U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Energy Efficient Mobility Systems

2023 Annual Progress Report

Vehicle Technologies Office

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Disclaimer

Acknowledgements

The Energy Efficient Mobility Systems (EEMS) Program would like to acknowledge all the researchers, participants, and stakeholders that contributed to and collaborated with the EEMS Program this past year.

Acronyms

2

21CTP	21st Century Truck Partnership
2D	two-dimensional

3

3D	three-dimensional

A

ACC	adaptive cruise control
ACE	actuated-coordinated eight-phase
ACM	American Center for Mobility
ACT	Application and Collaboration Tool
ADAS	advanced driver assistance system
ADOPT	Automotive Deployment Options Projection Tool
ADS	automated driving systems
AI	artificial intelligence
ALPR	automated license plate reader
AMBER	advanced model-based engineering resource
ANL	Argonne National Laboratory
ANN	Artificial neural network
APACK-I	Argonne Perception and Connectivity Kit-Infrastructure
APACK-V	Argonne Perception and Connectivity Kit-Vehicle
API	application programming interface
APR	Annual Progress Report
ATCS	active traffic control system
ATLAS	Automobile and Technology Lifecycle-Based Assignment
ATM	active traffic management
AV	automated vehicle
AVO	average vehicle occupancy

B

BDSM	Big Data Solutions for Mobility
BEAM	Behavior, Energy, Autonomy, Mobility
BEB	battery electric bus
BEV	battery electric vehicle
BL	binomial logit
BRT	Bus Rapid Transit

C

C&A	connectivity and automation

CACC	cooperative adaptive cruise control
CARTA	Chattanooga Area Region Transportation Authority
CAV	connected and automated vehicle; Cara-A-Van
CAVE	Connected and Automated Vehicle Environment
CAViL	Connected and automated vehicle-in-the-loop
CDA	Cooperative Driving Automation
CDS	curb data specification
CERPM	chip-enabled raised pavement markers
CI	connected infrastructure
C-ITS	Cooperative Intelligent Transportation System
CMU	Carnegie Mellon University
CO_2	carbon dioxide
CORE	Comprehensive Regional Evaluator
CoVaR	co-optimization of vehicles and routes
CRADA	Cooperative Research and Development Agreement
CSSP	cruising speed stop profile
CTE	controlled traffic event
CV	connected vehicle
C-V2X	cellular-vehicle-to-everything

D

$	Dollars (United States)
D3	Downloadable Dynamometer Database
DAC	disadvantaged community
DAQ	data acquisition
DCR	driver compliance rate
DCRNN	Diffusion Convolutional Recurrent Neural Network
DEMOS	Demographic Micosimulation
DGMARL	decentralized graph-based multi-agent reinforcement learning
DHE	Dependable Highway Express
DHM	Deep Hybrid Models
DL	deep learning
DOE	Department of Energy
DoEx	Design of Experiment
DOT	Department of Transportation
DSRC	dedicated short-range communications
DULPTAS	Delay, Urgency, trip Length, additional People, Time of day, Age, and Sex
DV	diesel vehicle
DVRP	dynamic vehicle routing problem

E

EEMS	Energy Efficient Mobility Systems
EERE	Energy Efficiency and Renewable Energy
e.g.	exempli gratia (for example)

EJ	environmental justice
eVMT	empty vehicle miles traveled
EPA	Environmental Protection Agency
EV	electric vehicle
EVSE	electric vehicle supply equipment
eVTOL	electric vertical take-off and landing

F

FASTSim	Future Automotive Systems Technology Simulator
FC	fuel consumption
FFC	fixed-time force-phase coordinated
FHWA	Federal Highway Administration
F-MEP	Freight mobility energy productivity
FOA	funding opportunity announcement
FOETT	Freight Operational Efficiency Technical Team
FOV	field of view
FSD	Full Self-Driving
FTA	Federal Transit Authority
FY	fiscal year

G

>	greater than
GB	gigabyte
GEH	Geoffrey E. Havers
GHG	greenhouse gas
GHz	gigahertz
GIS	geographic information system
GM	General Motors
GNN	graph neural network
GNSS	global navigation satellite system
GPS	Global Positioning System
GPU	graphics processing unit
GSA	General Services Administration
GFTS	General Transit Feed Specification
GUI	graphical user interface

H

HD	heavy-duty; high-definition
HDV	heavy-duty vehicle
HEV	hybrid electric vehicle
HIL	hardware-in-the-loop
HNN	hybrid neural network
HPC	high performance computing

HPS	hyperparameter search
HV	human vehicle
HVAC	heating, ventilation, and air conditioning
H-VIL	human-vehicle-in-the-loop
Hz	hertz

I

ICE	internal combustion engine
ICLV	integrated choice and latent variable
i.d.	id est (that is)
IDAS	Intelligent driver assistance system
INL	Idaho National Laboratory
IQR	interquantile range
ITS	intelligent transportation system

K

kg	kilogram
km	kilometer
KS	Kolmogorov-Smirnov
kW	kilowatt
kWh	kilowatt hour

L

L	litre
LBNL	Lawrence Berkeley National Laboratory
LD	light-duty
LDV	light-duty vehicle
LED	light-emitting diode
LiDAR	Light Detection and Ranging
LLR	low rolling resistance
LoRa	long-range
LR	linear regression
LTS	level of traffic stress
LVM	latent variable model

M

m	meter
MAE	mean absolute error
MAPE	mean absolute percentage error
MARL	multi-agent reinforcement learning
MB	megabyte
MBSE	model-based systems engineering
MD	medium-duty

MDS	mobility data specification
MEP	mobility energy productivity
MIL	model-in-the-loop
MIMO	multi-input, multi-output
min	minute
MIT	Massachusetts Institute of Technoloyg
MITIE	Micromobility Integrated Transit and Infrastructure for Efficiency
mL	milliliter
ML	machine learning
MPC	model predictive control
mph	miles per hour
MR	mixed reality
MRT	mixed reality tool
MTC	mobile traffic control
MTU	Michigan Technological University
MVT	MegaVander Test
MXL	mixed logit

N

NGSIM	Next-Generation SIMulation
NREL	National Renewable Energy Laboratory
NTCIP	National Transportation Communications for ITS Protocol

O

OBU	on-board unit
ODC	origin-destination
OEM	original equipment manufacturer
OpenPATH	Open Platform for Agile Trip Heuristics
OPEX	operational expense
OSM	OpenStreetMap
ORNL	Oak Ridge National Laboratories

P

%	percent
PDES	parallel-discrete event simulation
PDF	probability density function
PDR	packet drop ratio
PHEV	plug-in hybrid electric vehicle
PI	principal investigator
PMT	passenger miles traveled
PnD	perception and decision
PNNL	Pacific Northwest National Laboratory
PR	pooled rideshare

PRAM	polled rideshare acceptance model
PRS	Powertrain Recommender System
PTV	Planung Transport Verkehr

Q

Q1	first quarter
Q2	second quarter
Q3	third quarter
Q4	fourth quarter

R

R&D	research and development
rAVO	revenue average vehicle occupancy
RD&D	research, development and demonstration
RDD&D	research, development, demonstration, and deployment
RGB	red, green, and blue
RL	reinforcement learning
ROS	robotic operating system
RouteE	Route Energy Prediction Model
RPM	raised pavement marker
RSU	roadside unit
RTK	real-time kinematic
RyThMiCCS	Real-Time Mobility Communications and Control System

S

s	second
SAS	speed advisory system
SAUC	Sparsity-aware Uncertainty Calibration
SCAG	Southern California Association of Government
SEM	structural equation model
SOC	state of charge
SERPM	Southeast Florida Regional Planning Model
SIL	software-in-the-loop
SoS	systems of systems
SPaT	signal phase and timing
SQL	structure query language
SUMO	Simulation of Urban MObility
SVTRIP	Stochastic Vehicle Trip Profile

T

T3CO	Transportation Technology Total Cost of Ownership
TB	terabyte
TCO	total cost of ownership

TENA	test and training enabling architecture
TI	Technology Integration
TL	traffic light
TNC	transportation network company
TOU	time of use
TRB	Transportation Research Board
TRL	technology readiness level
TSC	traffic systems controllers
TSMS	Transit-centric smart mobility system

U

UCR	University of California, Riverside
UDDS	Urban Dynamometer Driving Schedule
UH	University of Hawaii
UI	user interface
U.S.	United States
USC	University of Southern California
U.S. DRIVE	Driving Research and Innovation for Vehicle efficiency and Energy sustainability
USF	University of South Florida
UTA	Utah Transit Authority
UTC	University of Tennessee at Chattanooga
UW	University of Washington; University of Wisconsin

V

V2I	vehicle-to-infrastructure
V2V	vehicle-to-vehicle
V2X	vehicle-to-everything
VD	vehicle delay
VECTOR	Visual-Enhanced Cooperative Traffic Operations
VIL	vehicle-in-the-loop
VMS	variable message sign
VMSATT	Vehicle and Mobility Systems Analysis Technical Team
VMT	vehicle miles traveled
VOICES	Virtual Open Innovation Collaborative Environment for Safety
VPPG	Virtual and Physical Proving Ground
VRP	vehicle routing problem
VTO	Vehicle Technologies Office
VTOL	vertical take-off and landing

W

W	watt
WMU	Western Michigan University
WTW	well-to-wheels

X

XIL	anything-in-the-loop

Y

YOLO	You Only Look Once

Z

ZEV	zero emission vehicle

Executive Summary

Our transportation system is changing. New, disruptive technologies such as connected and automated vehicles are being developed and introduced to the market. Innovative business models that provide car-sharing, ride-hailing, and micromobility services give new mobility options to consumers. Freight transport is evolving to meet the demands of a retail sector that is increasingly based on e-commerce. While this transition was already underway, the COVID-19 pandemic significantly disrupted the daily lives and activities of Americans, causing dramatic changes in highway congestion, public transit use, online purchasing, and attitudes about shared mobility options. By 2023, the transportation sector had largely rebounded from the initial impacts of the pandemic-related disruptions. The permanence of these changes remains to be seen and their effects must be considered in the research, development, and deployment of new mobility solutions.

The shifting mobility landscape offers opportunities to improve the economic and energy productivity of the U.S. transportation sector, while advancing the safety, affordability, and accessibility of transportation for all Americans. The U.S. Department of Energy (DOE) Office of Energy Efficiency and Renewable Energy (EERE) Vehicle Technologies Office (VTO) created the Energy Efficient Mobility Systems (EEMS) program to understand the range of mobility futures that could result from disruptive transportation technologies and services and to create solutions that improve energy efficiency, increase convenience, and lower cost of transportation through: (1) research, development, and demonstration (RD&D) at the vehicle, traveler, and system levels; and, (2) creating new knowledge, tools, insights, and technology solutions that increase mobility energy productivity (MEP) and decrease greenhouse gas and pollutants emissions for individuals and businesses. EEMS program activities during fiscal year (FY) 2023 focused on analytical research, development of vehicle and infrastructure controllers, and large-scale modeling and simulation to understand the impacts that new mobility technologies and services will have at the vehicle-, traveler-, and overall transportation system-level. This research included the continued development of a multi-fidelity, end-to-end transportation system models and tools to evaluate the complex interactions among the various actors within the mobility landscape, analysis of empirical data to characterize which solutions may provide the largest benefits, and development of new control systems and algorithms that use vehicle connectivity and automation to improve the performance and efficiency of individual vehicles as well as the overall traffic system. Each of these capabilities will ultimately be deployed to end-users, technology integrators, and other stakeholders so that their impact can be realized.

This document presents a brief overview of the EEMS program and documents progress and results from projects within each of the EEMS activity areas. The Computational Modeling and Simulation key activity area summarizes work within the sub-areas of (1) the SMART (Systems and Modeling for Accelerated Research in Transportation) Mobility Lab Consortium, (2) Artificial Intelligence, High-Performance Computing, and Data Analytics, and (3) Core Simulation and Evaluation Capabilities. Additionally, the program's advanced RD&D projects are summarized within (4) the Connectivity and Automation Technology key activity area. Each of the individual progress reports provides a project overview and highlights of the technical results.

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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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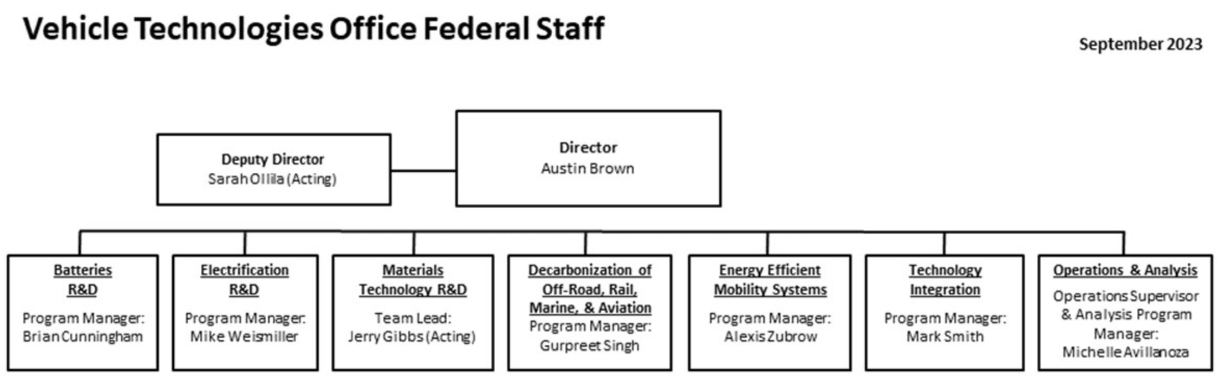
[1] Bureau of Transportation Statistics, DOT, Transportation Statistics Annual Report 2020, Table 4-1, https://www.bts.gov/tsar.
[2] Davis, Stacy C, and Robert G Boundy. Transportation Energy Data Book: Edition 40. Oak Ridge, TN: Oak Ridge National Laboratory 2022. https://doi.org/10.2172/1878695. . 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



Energy Efficient Mobility Systems Program Overview

Introduction

On behalf of the EEMS program of DOE's EERE VTO, we are pleased to submit this Annual Progress Report (APR) for Fiscal Year (FY) 2023.

The introduction of disruptive transportation technologies and services, such as connected and automated vehicles, car-sharing, ride-hailing, and micromobility services, provides new, low-cost mobility options for consumers. Additionally, the evolving retail sector, shaped by the convenience of online shopping, has resulted in not only a shift in how we transport and deliver goods, but it has also had ripple effects in personal transportation. This transforming mobility landscape presents a significant opportunity to improve economic and energy productivity and advance safety, affordability, accessibility, and equity in the transportation sector. However, while these changes can provide benefits to the American public, they also present risks, challenges, and questions that must be addressed.

The mobility transformation was abruptly altered in 2020, as the COVID-19 pandemic significantly disrupted the daily lives and activities of Americans, resulting in dramatic changes in highway congestion, public transit use, online purchasing, and attitudes about shared mobility options. Americans saw the transportation sector rebound during 2021, through 2022, and continue in 2023. Micromobility use surpassed or matched pre-COVID usage levels in many cities. Modes such as public transit and ridehail continue to struggle; however, this cannot fully be attributed to the COVID-19 pandemic since there are other factors that contribute to the use of these modes. The permanence of these changes remains to be seen and their effects must be considered in the research, development, and deployment of new mobility solutions.

DOE conducts research to understand how the changing mobility landscape will affect transportation energy consumption and identifies opportunities to create more efficient, affordable, reliable, accessible, equitable, and secure transportation options that enhance mobility for individuals and businesses. Within EERE, the EEMS program is responsible for this research portfolio.

This APR describes work that the EEMS program conducted during FY 2023 in support of the EEMS program goals as described in the following section.

Mission and Goals

The EEMS Program supports VTO's mission to improve transportation energy efficiency through low-cost, secure, and clean energy technologies. EEMS conducts research, development, and demonstration (RD&D) at the vehicle-, traveler-, and system-levels, creating knowledge, insights, tools, and technology solutions that increase mobility energy productivity and decrease greenhouse gas and pollutants emissions for individuals and businesses. This multi-level approach is critical to understanding the opportunities that exist for optimizing the overall transportation system and providing mobility access in every community. The EEMS program uses this approach to develop tools and capabilities to evaluate the energy impacts of new mobility solutions and to create new technologies that provide economic benefits to all Americans through enhanced mobility.

Through its SMART Mobility Laboratory Consortium, the EEMS program developed an accessibility metric known as *mobility energy productivity*. Because EEMS aims not only to reduce the energy consumed in the transportation system, but also to reduce the time and cost associated with moving people and goods while improving access to mobility, a comprehensive metric that incorporates all three factors (energy, time, and cost) is required. MEP is used as one lens through which the EEMS program can evaluate the mobility impacts that potential technologies and services may have and by which program success can be measured as it develops new mobility solutions.

The EEMS program works towards achieving three strategic goals in order to reach the program's overall goal of ***identifying critical pathways and developing innovative technology solutions to enable significant improvements in mobility energy productivity and reductions of greenhouse gas and pollutant emissions when adopted at scale***. Each strategic goal is discrete, but all three goals are interrelated such that the success in any one goal furthers the achievement of the other two.

STRATEGIC GOAL #1: Develop new tools, techniques, and core capabilities to understand and identify the most important levers to improve the energy productivity and reduce the greenhouse gas and pollutant emissions of future integrated mobility systems.

STRATEGIC GOAL #2: Identify and support RD&D to develop innovative technologies that enable energy efficient future mobility systems.

STRATEGIC GOAL #3: Share research insights and coordinate and collaborate with stakeholders to support energy efficient local and regional transportation systems.

Program Organization

To achieve its programmatic goals, the EEMS program implements four coordinated areas of focus, each with its own set of projects. Each of these four research areas directly supports at least one of the three EEMS strategic goals. The four research areas are:

- SMART Mobility Laboratory Consortium
- Artificial Intelligence, High-Performance Computing, and Data Analytics
- Core Simulation and Evaluation Capabilities
- Connectivity and Automation Technology.

The first three areas are grouped within the "Computational Modeling and Simulation" key activity, while the "Connectivity and Automation Technology" area represents its own key activity.

SMART Mobility Lab Consortium

The SMART Mobility Laboratory Consortium is a multi-year, multi-laboratory collaborative dedicated to further understanding the energy implications and opportunities of advanced mobility solutions. In FY 2023, the EEMS Program's "SMART Mobility 2.0" fully matured, building upon the research results and insights from the first phase of SMART Mobility. This phase included an increased emphasis on development, improvement, and deployment of the SMART Mobility Integrated Modeling Platform and a concentrated effort on research, development, and evaluation of connected and automated vehicle control algorithms. Additionally, SMART Mobility 2.0 included several research projects on various aspects of the transportation system (e.g., micromobility, transit, curb management, and drones) that inform the integrated SMART Mobility modeling platform. Results from the consortium were presented in a webinar series.

The SMART Mobility Laboratory Consortium is the EEMS program's primary effort to create tools and generate knowledge about how future mobility systems may evolve and identify ways to reduce their energy intensity. The consortium also identifies R&D gaps that the EEMS program may address through its research portfolio. Furthermore, the tools and insights created through the SMART Mobility Laboratory Consortium are shared with a variety of mobility stakeholders, including technology developers, automotive manufacturers, local governments, and transportation planning organizations.

Artificial Intelligence, High-Performance Computing, and Data Analytics

The EEMS Program conducts research to develop and apply the national laboratories' capabilities in artificial intelligence (AI), high-performance computing (HPC), and data analytics to various transportation problems. The use of these tools assists in the design, planning, and operation of future mobility systems at multiple scales. HPC helps manage, store, analyze, and visualize conclusions from big data. AI serves to recognize patterns and extract actionable information to answer transportation-related questions through predictive data analytics applied to both vehicle/infrastructure (i.e., physical) data and human decision-making (i.e., behavioral) data.

The program's efforts in this area include the development of scalable data science and HPC-supported computational frameworks needed to build next-generation transportation/mobility system models and operational analytics that leverage the availability of near-real-time data and run quickly. This includes multi-lab efforts focused on developing city/regional-scale "digital twins" of the transportation system, providing real-time awareness of the state of the highway system (e.g., traffic flow and volumes). These models can then be used to develop control systems that improve congestion and reduce energy consumption (e.g., by implementing adaptive traffic signal control or optimal routing of individual vehicles). Additionally, the EEMS Program supports research to apply deep-learning techniques for sensing, perception, and control of automated vehicles (AVs), expedite the development and increase the performance and efficiency of AV control algorithms, and implement virtual test environments to support the development of resilient AV control systems.

The AI, HPC, and data analytics area merges large-scale transportation data sets from public and private entities with unparalleled computational and analytical resources at the national laboratories to develop actionable solutions to specific transportation energy challenges faced by cities, states, and regions across the U.S. These solutions enable local stakeholders to plan and operate their transportation systems in a way that improves energy efficiency as their populations grow and new mobility options become available. In doing so, it directly supports all three EEMS strategic goals.

Core Simulation and Evaluation Capabilities

VTO has successfully conducted hardware evaluations of component and vehicle technologies, developed vehicle systems models based on the results of these evaluations, and performed simulation and analysis of potential vehicle powertrain solutions built upon these models. The EEMS program develops and maintains these critical capabilities within the National Laboratory system in order to test, evaluate, model, and simulate advanced components, powertrains, vehicles, and transportation systems. These capabilities include vehicle and component test procedure development, highly instrumented hardware evaluation, controls algorithm validation, high-fidelity physical simulation, and transportation data management and analysis. As individual vehicles become more connected (with each other and with transportation infrastructure) and increasingly automated, new evaluation capabilities such as anything-in-the-loop (XIL) test environments will be necessary to support the EEMS program in evaluating the energy and mobility outcomes of future transportation systems and for other VTO R&D programs in quantifying the performance and efficiency benefits of specific powertrain technologies under development.

The suite of core VTO evaluation and simulation capabilities is critical to the EEMS program's ability to understand the impacts of future mobility and is also important in identifying research opportunities and producing insights to share with mobility stakeholders.

Connectivity and Automation Technology

The EEMS program's Connectivity and Automation Technology RD&D focuses on innovative and scalable mobility projects and targeted system-level opportunities to reduce the energy intensity of the movement of people and goods through connected and automation transportation solutions. The program partners with industry and academia to research and develop technology solutions that lead to mobility improvements through advancements in hardware, software, control systems, advanced sensing and computing, infrastructure, and powertrain components. Competitive funding opportunity announcements (FOAs) solicit project proposals for both passenger and transit vehicles to develop technology solutions that progress the state-of-the-art towards the EEMS program's targets. Through cost-shared cooperative agreements, FOAs provide external stakeholders the opportunity to develop innovative and disruptive solutions that the private sector would not otherwise consider due to their risk or uncertainty of return-on-investment, but which could result in public benefits if successful. These solicitations may be broad in scope, calling for a wide variety of proposals for technology development efforts across a range of potential concepts, or may specifically target an explicitly defined research concept. Additionally, the EEMS program solicits RD&D proposals from the national laboratories through periodic lab calls and directly initiate targeted projects with individual labs or lab consortia to leverage specific lab capabilities.

The Connectivity and Automation Technology portfolio directly supports EEMS strategic goals by developing innovative technology solutions for mobility—the results of which inform the analytical work to understand the impacts of these new technologies and are disseminated to the stakeholder community.

Coordination

The EEMS program coordinates its activities with other programs within VTO, as well as with other federal agencies, industry stakeholders, and other members of the mobility research community.

VTO's Technology Integration (TI) program works with cities and stakeholders to demonstrate and evaluate new mobility technologies in the field and collect data through "Living Labs" pilot projects. These projects are an important feedback mechanism to EEMS R&D and provide a source of real-world data to test, validate, and improve models, simulations, software, and hardware. The EEMS program coordinates with the TI program, collaborating with stakeholders to support city and regional efforts to develop energy efficient transportation systems through key elements of an implementation strategy: stakeholder engagement, demonstration projects, and technical assistance. As an example of the close coordination between EEMS and TI, the two programs jointly funded an Area of Interest in VTO's FY 2021 Program-Wide FOA entitled, "Implementation of Energy Efficient Mobility Systems Technologies into Real-World System Applications" which led to project kickoffs and active collaboration across programs through 2022 and 2023.

Coordination between EEMS and other federal programs focused on connected, automated, and efficient transportation systems is critically important. EEMS participates in planning discussions within multiple offices within DOE (e.g., ARPA-E) and with various modal administrations within U.S. Department of Transportation (DOT), including the Federal Highway Administration (FHWA), Federal Transit Administration (FTA), and the Intelligent Transportation Systems Joint Program Office (ITS-JPO). Coordination with U.S. DOT is important due to the linkage between VTO's R&D activities to create efficient, secure, and sustainable transportation technologies, and U.S. DOT's mission to ensure our nation has the safest and most efficient and modern transportation system in the world.[7]

In addition to intergovernmental collaboration with the U.S. DOT, the EEMS program coordinates with industry partners. For example, U.S. DRIVE (Driving Research and Innovation for Vehicle efficiency and Energy sustainability) is a non-binding and voluntary government-industry partnership focused on advanced automotive and related energy infrastructure technology R&D.[8] EEMS participates in U.S. DRIVE through the Vehicle and Mobility Systems Analysis Technical Team (VMSATT) to identify the most promising areas of pre-competitive mobility research of interest to the government, automotive industry, energy sector, and utility company partners. Additionally, the EEMS program coordinates with the medium- and heavy-duty trucking and freight industry through the 21st Century Truck Partnership (21CTP)[9], by pursuing collaborative R&D to realize its vision for our nation's trucks and buses to safely and cost-effectively move larger volumes of freight

[7] https://www.transportation.gov/about
[8] https://www.energy.gov/eere/vehicles/us-drive
[9] https://www.energy.gov/eere/vehicles/21st-century-truck-partnership

and greater numbers of passengers while emitting little or no pollution. The EEMS program is directly involved with the Freight Operational Efficiency Technical Team (FOETT) within the truck partnership.

The EEMS program continually seeks additional high-value opportunities to engage with relevant stakeholders in order to share EEMS-funded research results and learn from other mobility-related efforts. For example, in FY 2023 the EEMS program was a governmental sponsor and member of the National Academies/Transportation Research Board Forum on Preparing for Automated Vehicles and Shared Mobility[10], which brings together public, private, and other research organizational partners to share perspectives about how the deployment of automated vehicles and shared mobility services may dramatically increase safety, reduce congestion, improve access, enhance sustainability, and spur economic development. This forum concluded in 2023. The SMART Mobility Laboratory Consortium also convened an Executive Advisory Board, comprised of experts and decision-makers representing the automotive industry, technology companies, academia, non-governmental organizations, non-profits, and other transportation-related associations. This board provided input and review to the research conducted by the Consortium and helped ensure the work performed was aligned with a variety of mobility stakeholders. As the Consortium focused on completing and deploying its integrated modeling workflow during SMART Mobility 2.0, it pursued collaborations and partnerships with local city governments, transportation planning organizations, and other stakeholders to inform transportation policy making, including by hosting a series of webinars to highlight the insights from SMART 2.0.[11]

Project Funding

VTO selects and funds critical research through a combination of competitive FOA selections, and direct funding to its national laboratories. Competitive FOA projects are fully funded through the duration of the project in the year that the funding is awarded. Funding for direct-funded and competitive award projects are contingent on annual Congressional budget appropriations.

Research Highlights

EEMS SMART Mobility 2.0

- Multimodal Travel: Transit and Ride Hail: During FY 2023, researchers analyzing transit found optimization improves ridership up to 11% at moderate cost and increases transit service can have significant impacts on energy and greenhouse gases in targeted areas. Additionally, approximately 50% transit electrification requires an approximate 20% fleet increase to maintain schedules. These results indicate suburban agencies could focus on increasing frequency and agencies operating in high density urban areas could implement new routes and bus rapid transit. Regarding ride hail, researchers found vehicle miles traveled (VMT) can be reduced up to 3% with pooling and geofencing, and 11% with corner-to-corner. Researchers also found lower prices can increase solo ride hail but can also decrease pooling while the lowest income travelers benefit disproportionally when ride hail fleets compete and prices reduce. This indicates fleet operators could incentivize corner-to-corner in dense urban areas and encourage pooling while considering its limits when expanding services.

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[10] https://www.nationalacademies.org/our-work/forum-on-preparing-for-automated-vehicles-and-shared-mobility-services

[11] https://www.energy.gov/eere/vehicles/articles/eems-smart-mobility-capstone-reports-and-webinar-series

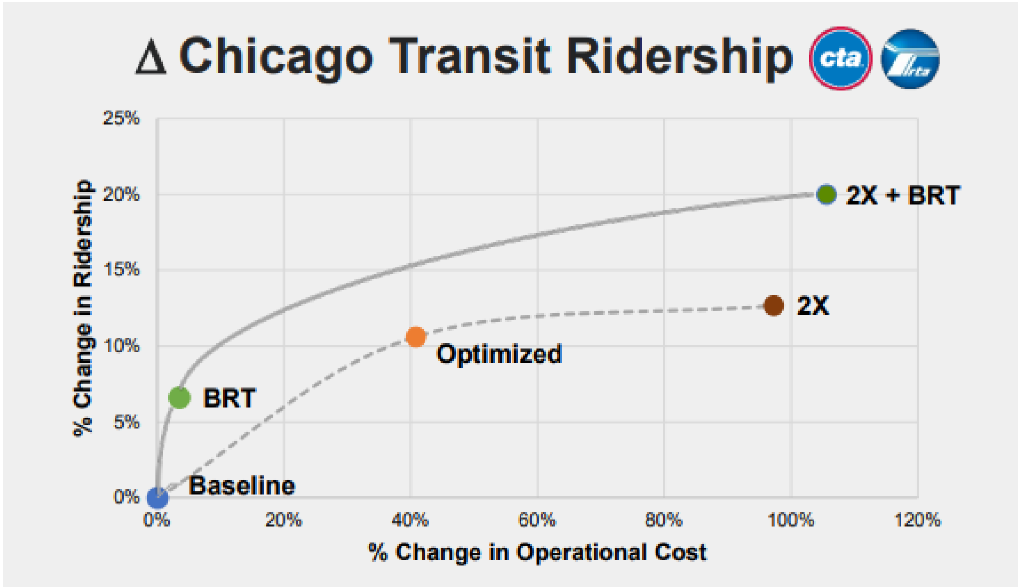

Figure 1. Increased bus frequences or new Bus Rapid Transit (BRT) improves transit user experience.

- Multimodal Travel: Micromobility & Drones: Micromobility researchers found that shared micromobility is a viable replacement for many trip types and the energy benefits outweighing the energy costs. Access to e-bikes may improve mobility as measured by mobility energy productivity (MEP). To foster these findings, e-bike rebate programs could be encouraged to replace vehicle use. Researchers also found drone use can offer improved energy use and efficiencies over ground vehicles in local deliveries while larger vertical take-off and landing (VTOL) aircraft can enable improved rural solutions. This indicates delivery providers could improve services, reduce delivery time, and reduce energy by using drones.

- Connected and Automated Vehicles (CAVs): Currently, non-automated (or manual) driver behavior is often energy inefficient. For example, actions like cut-ins and excessive lane changes lead to increased energy consumption. Additionally, production ADS and advanced driver assistance system (ADAS) is focused primarily on safety, leading to potential energy penalties. In the future, representative scenarios are critical to estimate CAVs' energy impact to enable the goal of at least 25% energy savings.

- Connected and Automated Vehicles (CAVs) and Intelligent Transportation Systems: Researchers found connectivity and automation can improve mobility, but fully automated driving increases congestion, energy, and emissions. Vehicle-to-everything (V2X) can improve mobility and energy through better signal coordination, better routing, and better trajectory planning. Curb access and productivity can be maximized by placing passenger loading zones and commercial vehicle loading zones on different but adjacent streets. During FY 2023, analysis showed vehicle technology improvements account for 70% of energy reduction, and mobility and operations are 30%. Also, airports can attain significant improvements in on-road traffic congestion through automation of variable message signs saving 30-80 vehicle hours per hour and 90-360 kg of CO_2 per hour.

- Freight: Researchers found freight could be positively and negatively impacted by automation (e.g. driving time restrictions vs. increased VMT from passenger cars) and that advanced vehicle technologies are critical to mitigating energy and emissions impact from freight growth. New modes and services have a critical role to play: bikes for on-demand deliveries and drones for last mile deliveries. Policies and continuous R&D are critical to accelerate truck electrifications market penetration. Collaboration across stakeholders to simultaneously support advanced vehicle technologies adoption along with electric vehicle support equipment deployment and electric grid upgrades is vital.

- Electrification: Researchers found vehicle technology R&D and polices are critical to accelerate zero emission vehicle (ZEV) sales and reduce income disparity in ZEV ownership. Addressing system level considerations from vehicle design/usage to electric vehicle support equipment location/usage and electric grid impacts are critical for success. Additionally, electrification plays a key role for equity by reducing emission and noise while providing reductions in total cost of ownership when compared to other powertrains.

Micromobility Integrated Transit and Infrastructure for Efficiency (MITIE) (Lead: National Renewable Energy Laboratory)

- This project expanded the spectrum of modes currently being researched withing SMART by exploring micromobility (e-scooters, bicycles, e-bikes, and electric scooters) as an important tool toward meeting energy-efficiency goals. Micromobility is a viable replacement for many trip types. In FY 2023, researchers performed a MEP analysis of e-bike mode using data from the Colorado Energy Office program, which provides e-bikes to low-income users. The ratio of e-bike MEP to drive MEP shows e-bikes score >50% the magnitude of driving in some settings. Additionally, e-bikes can provide as much as 80% of the quality of mobility provided by a much faster mode, such as driving. This indicates communities could continue to encourage e-bike deployments as one of multiple mobility options to replace driving for certain trips.

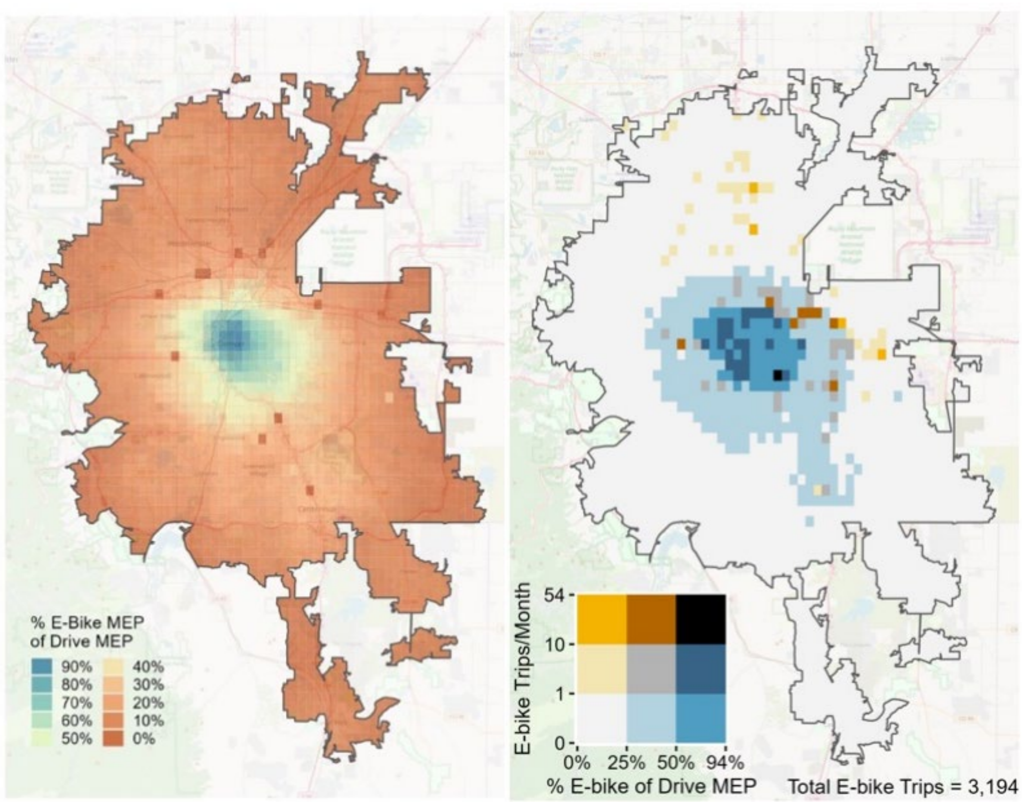

Figure 2. MEP evaluation shows that e-bikes can replace the utility of private automobiles in some locations.

Improved Mobility and Energy Savings Through Optimization of Cooperative Driving Automation (CDA) Application for Signal Controls for Arterial Mixed Traffic Scenarios (Lead: Lawrence Berkeley National Laboratory)

- Connection is the key to integrate vehicle and highway automation in a large transportation system to optimize the energy consumption, emissions, mobility, and other factors such as safety. The overall goal of the project is the application of CDA technologies, such as cooperative adaptive cruise control (CACC)/platooning and their application for mixed-traffic management on arterials (with connected traffic controllers) and freeways for energy savings, emissions reductions, and mobility improvements. In FY 2023, researchers finalized the Concept of Operation, the design of the experimental setup, at a test track. The traffic signal control algorithm uses a model predictive control approach which has been implemented in Aimsun as an application program interface. Argonne National Laboratory successfully completed the CAN override development for three selected test vehicles encompassing various powertrains (internal combustion engine, hybrid, and electric). This capability grants full authority over the vehicle commends and allows testing and experimentation of CACC control algorithms.

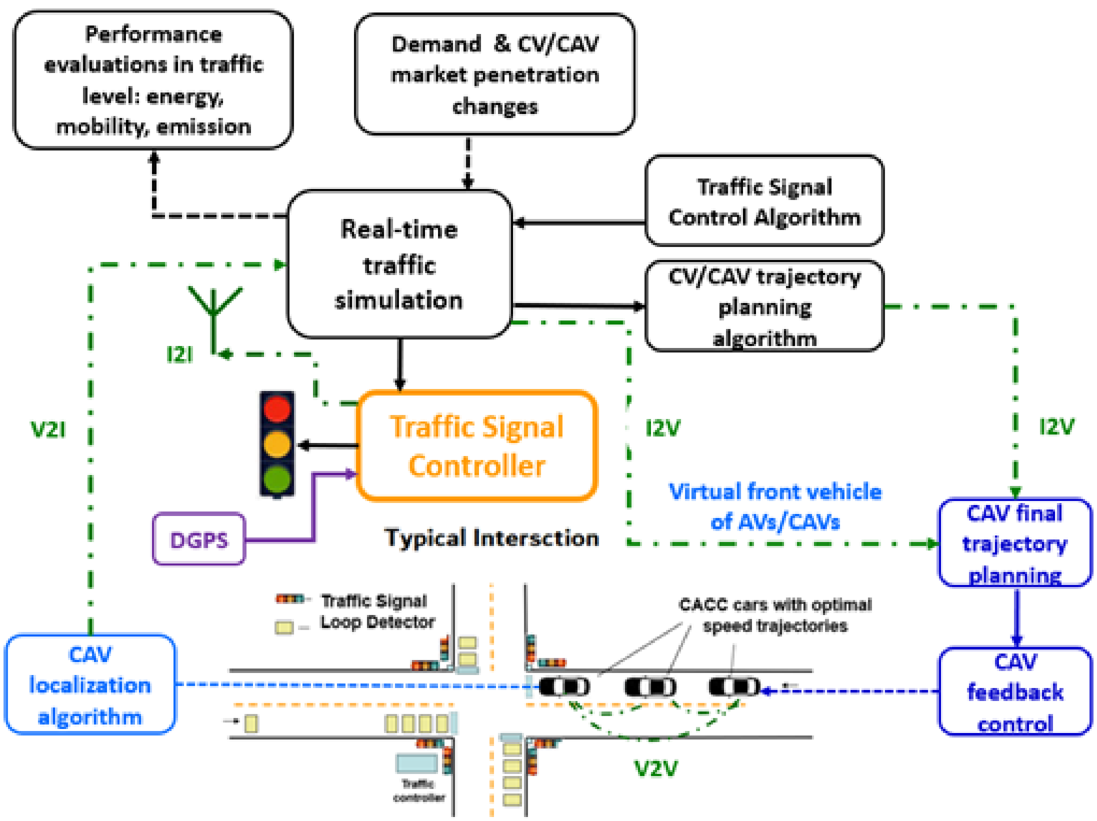

Figure 3. Finalized overall system picture for the Concept of Operation

Developing an Energy-Conscious Traffic Signal Control System for Optimized Fuel Consumption in Connected Vehicle Environments (University of Tennessee at Chattanooga)

- This project aims to address the energy related challenges associated with adaptive traffic control systems by integrating connected vehicles and connected infrastructure. Specifically, a connected vehicle-based adaptive traffic control system that improves fuel consumption in mixed traffic environments will be developed. In FY 2023, researchers focused on testing the proposed eco-adaptive traffic control system (Eco-ATCS) in the field. To achieve that, researchers modified data resources to mitigate the existing 1 min delay, enhanced data integration, updated the ecological performance index, which considers the impact of several operating conditions that impact fuel consumption footprints at signalized intersections (vehicle type, speed, grade),to include multiple vehicle types, transitioned from hardware-in-the-loop to software-in-the-loop, fine-tuned the proposed reinforcement learning-based Eco-ATCS algorithm to include pedestrian and bus, and performed several rounds of testing in the field. Eleven intersections were connected in Vissim to SEPAC m60 controllers. Eleven virtual controllers were connected with default signal timing plans to verify the established connection. Once the connection was established through assigned port number, TACTICS software was used to upload field signal timing plans for all 11 intersections.

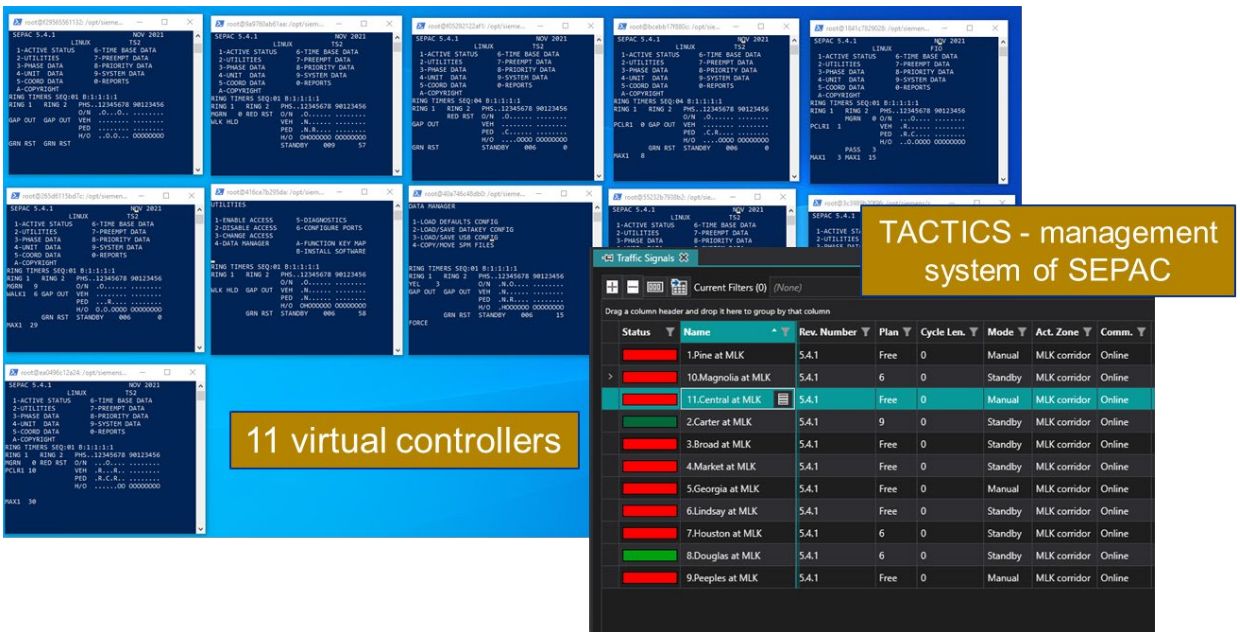

Figure 4. SEPAC software-in-the-loop.

Optimizing Drone Deployment for More Effective Movement of Goods (Idaho National Laboratory)

- Aerial drones offer a distinct potential to improve the delivery of goods in the last mile, specifically for time-sensitive, small, and localized deliveries. The effectiveness and importance of such services was noted to be higher in many more rural areas, where drones may allow the regular delivery of time sensitive goods like medication. This project's goal is to answer critical questions about how aerial drones can be deployed to deliver goods most efficiently and enable strategic improvements in the whole mobility system. In FY 2023, researchers examined the impacts of a mixed fleet of air and ground vehicles in the process of providing a realistic and full-service delivery service. Weather impacts on the availability of each class of drone and its ability to perform deliveries was investigated. Three locations (Idaho Falls, Idaho; Chicago, Illinois; San Francisco, California) were examined to determine if temperatures would prevent flying for part or all of the day, whether wind levels would be higher than allowable values for longer than 5 min, and whether there were more than trace amounts of precipitation.

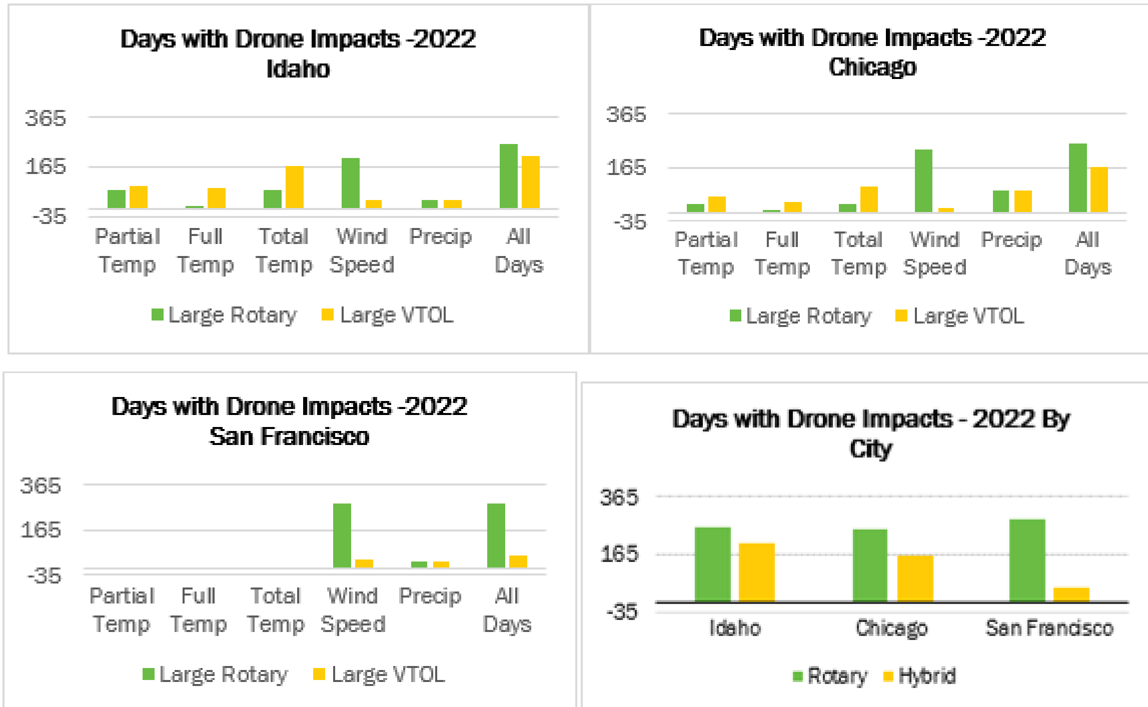

Figure 5. Number of days with impacts from weather in different locations.

BEAM CORE (Lawrence Berkeley National Laboratory; National Renewable Energy Laboratory)

- Behavior, Energy, Autonomy, Mobility (BEAM) Comprehensive Regional Evaluator (CORE) is a suite of integrated models to understand technology and policy changes on a comprehensive intermodal system. In FY 2023, researchers studied how the implementation of four new transit projects in the San Francisco Bay Area might shift travel mode of individuals using the new projects and analyzed the potential impacts of more ride-hail fleets with larger fleet sizes and lower prices in the San Francisco Bay Area. An analysis on the impact of zero emission vehicles, consolidated deliver, and increased e-commerce demand on freight energy consumption in the Austin, Texas region was also investigated along with the impact of technology progress as well as polices (including mandates, tax credits, and rebates) on the penetration of zero emission light-duty vehicles in the San Francisco Bay Area. Several of these studies included an analysis of distributional outcomes in the populations and equity considerations. Additional results on income-based cordon pricing, telecommuting, and additional transit expansion and freight results were also presented.

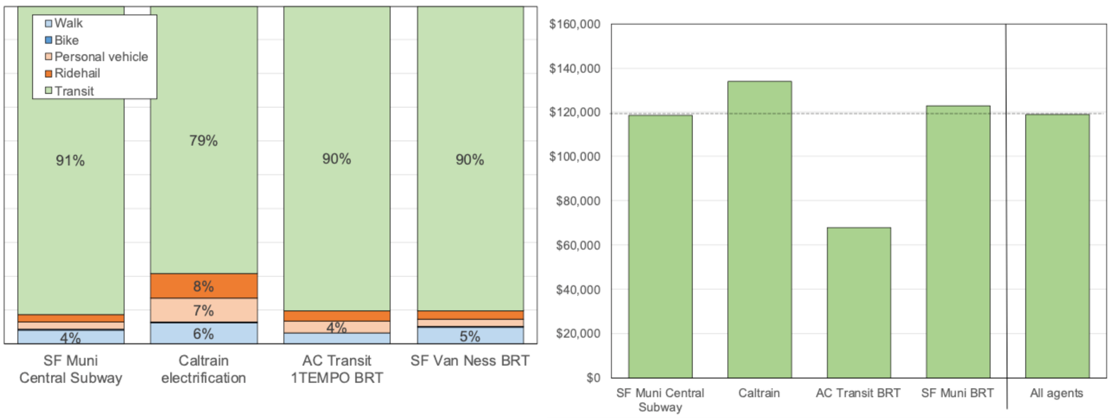

Figure 6. Simulated transit expansion in the San Francisco Bay area

We are pleased to submit the APR for the EEMS program for FY 2023. Inquiries regarding the EEMS Program and its research activities may be directed to the undersigned.

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I Computational Modeling and Simulation

I.1 SMART 2.0

I.1.1 SMART 2.0 Energy Efficient Connected and Automated Vehicles Model and Workflow (Argonne National Laboratory)

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Start Date: October 1, 2020 End Date: June 30, 2024
Project Funding: $6,850,000 DOE share: $6,850,000 Non-DOE share: $0

Project Introduction

Driving automation features are increasingly available on production cars. In 2020, 9% of new cars sold in the United States had Level 2 automation, and 51% had Level 1 automation [1], promising greater convenience and safety. Vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication technology (or V2X) are also actively under consideration for safety and system-level traffic improvements. Automation and connectivity also can be used for greater energy efficiency: vehicles can use the information about surrounding and future road environment provided by sensors and V2X to minimize loss of kinetic energy, better manage on-board energy, and maximize powertrain efficiency. Under the SMART 1.0 program, we developed several such energy-focused automated driving controllers, e.g., “speed-only” optimization [2] and “speed+powertrain” co-optimization [3]. Using RoadRunner, a high-fidelity simulation framework that we developed specifically for research on energy efficiency for connected and automated vehicles (CAVs), we performed a large-scale simulation study applying the algorithms and demonstrated up to 22% savings [4].

Research on CAV is primarily driven by safety, and existing research on CAV energy control often has been limited to narrow-use cases, assumed perfect knowledge of the future, and/or used computationally intensive algorithms that cannot be implemented in the real world. To be adopted at scale, controls need to be deployable on real-time control units, adapt to quickly changing environments, and work for a broad range of road and traffic conditions. We addressed some of these barriers in foundational SMART 1.0 work, but several research gaps remained: limited types of vehicles, lack of realistic traffic, the need for manual calibration, and the lack of real-world demonstration. In this project, we address these gaps through implementable and robust controls using a combination of optimal control, model-predictive control, and Artificial Intelligence (AI). The design, implementation, and validation of these controls relies on the improved and expanded Argonne-led SMART 2.0 workflow, leveraging new developments in RoadRunner as well as the new XIL capability that enables the testing of the controls in real systems. We also address the lack of well-defined practical methods to evaluate CAV real-world energy impacts, which discourage manufacturers from developing and deploying energy-saving features using connectivity and automation (C&A) technologies.

Objectives

The overarching goal is to demonstrate significant and consistent energy savings through vehicle and powertrain controls enabled by connectivity and/or automation. Specific objectives are listed below.

<u>**Objective 1**</u>**: Develop scalable, robust, intelligent, and implementable CAV controls for energy efficiency**. Building on algorithms developed in SMART 1.0, we will develop controls that are *scalable*, i.e., can be deployed across vehicle types, classes, various combinations of powertrains, and C&A technology implementations; *robust* to external disturbances such as traffic conditions, road geometry, and observation errors; *implementable* in real-world vehicles; and *intelligent*, i.e., able to learn from experience using AI. This objective is achieved through work in Task 1.

<u>**Objective 2**</u>**: Quantify energy savings from CAV controls** on a large number of real-world scenarios through large-scale simulations using RoadRunner and other SMART tools with various automation, connectivity, powertrain, road, traffic, and VTO technology target assumptions. This will guide scenario selection for real-world testing and validation. This work is to be carried in Task 2.

<u>**Objective 3**</u>**: Demonstrate and validate the energy savings from CAV controls on real-world vehicles.** We will use various hardware platforms and facilities developed as part of other DOE and DOT projects. Multiple vehicles and test setups, from on-dynamometer to on-track and on-road, will be used to test different controls on selected scenarios and to validate the energy savings observed in simulation. Tests will be led at Argonne National Laboratory (ANL) or by our partners (Michigan Technological University [MTU], the American Center for Mobility [ACM], Clemson University, or the University of South Florida [USF]) as part of Task 2.

<u>**Objective 4:**</u> **Develop generic methodology to quantify the average real-world energy impact of C&A technologies.** This methodology will benefit the industry at large by enabling original equipment manufacturers (OEMs) and researchers to quantify their connected/automated driving technologies from an energy point of view, whether at the advanced research/concept phase or at the validation stage. This is done in Task 3.

Approach

The project is organized in three tasks, as shown in Figure I.1.1.1. Task 1 focuses on developing new controls, which are then evaluated through large-scale simulation and XIL in Task 2. Task 3 leverages real-world driving and proposes a methodology to quantify the energy impacts of C&A technologies.

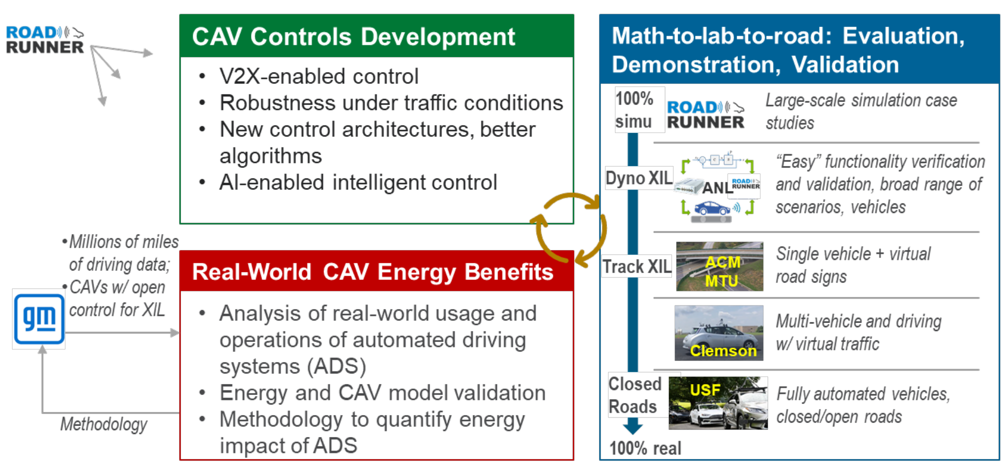

Figure I.1.1.1 Development and validation of intelligent CAV controls for energy efficiency (project approach).

In Task 1, we develop novel controls generating energy savings from connectivity, sensors, and automation and address the research gaps identified at the conclusion of SMART 1.0 as follows.

1. We research how V2X connectivity can enable energy savings. We expand beyond the SMART 1.0 program V2I case (traffic light eco-approach of the next traffic light), for example, by adding V2V communications and long-range V2I communications.
2. We investigate the robustness of the controls under more realistic traffic conditions and improve them accordingly.
3. We experiment with different types of control architecture and powertrain types.
4. We explore how AI can be used for eco-driving control.

All new developments are evaluated in RoadRunner, the development of which is done in the *SMART 2.0 ANL Workflow / New Features* project.

Task 2 centers on the evaluation, demonstration, and validation of the controllers developed in Task 1, from large-scale simulation studies to testing in real vehicles. Various experimental setups are used, and most of them rely on the XIL concept, where real and virtual systems are tested in a closed-loop fashion. The newly developed Argonne XIL workflow enables controls testing on a vehicle positioned on a chassis dynamometer driving within a virtual environment simulated by RoadRunner. On-track XIL testing is performed at the ACM on vehicles prepared by MTU and ACM, focusing on a single-vehicle scenario in various emulated urban driving situations. On-track XIL experiments led by project partner Clemson University will feature multi-vehicle and in-traffic scenarios. Finally, project partner USF will conduct tests using Level 3 automated vehicles. In each case, we create "digital twins" of the road and vehicles in RoadRunner, implement the controls in the experimental vehicles, test for functionality, and then validate the energy savings predicted by the simulations.

In Task 3, we work towards a methodology to quantify the energy benefits of automated driving technologies through a combination of simulations and hardware testing. General Motors (GM) is a Cooperative Research and Development Agreement (CRADA) partner for this task and provides real-world driving data from fleet vehicles equipped with automated driving technology.

Results

AI-enabled intelligent control for CAVs. Eco-driving using controllers developed in the SMART program were shown to lead to considerable energy savings. These controls use various control and optimization techniques, but certain key parameters still require manual calibration, and are kept constant during the trip and not optimized across different situations. We therefore leveraged AI, reinforcement learning (RL) specifically, to work in tandem with our existing eco-driving controller and improved its performance by optimizing the control parameters on the go–this is the "RL-combined controller". In FY 2023, we sought to put in place the RL tools that will enable us to demonstrate the RL-combined controller in a broad range of scenarios. Accomplishments include:

1. Development of new RL agents that are equipped with continuous-action-space RL algorithms such as proximal policy optimization and deep deterministic policy gradient. Compared to previous RL agents, they have the capability to handle more sophisticated problems and scenarios.

2. New RL implementation workflow that supports parallel computing and graphics processing unit (GPU) training, leading to 10 times faster training than previous method. In addition, RL implementation workflow was designed to automate the RL agent training process to the greatest extent.

3. Demonstration of the workflow's efficacy and evaluation of the resulting RL-combined control in the synthetic route.

As is shown in Figure I.1.1.2, the performance of RL-combined control optimizing one parameter is demonstrated in a synthetic route in RoadRunner. Compared to a human driver model and manually calibrated controller, RL-combined controller leads to resp. 3.5% and 2.1% faster travel time and resp. 9.4% and 3.7% lower energy consumption. We will complete this task in FY 2024 through larger-scale demonstration of the RL-combined eco-driving control.

Controllers	Total Time (s)	Total Energy (J)
Human Driver	186.50	9.62 x 10^5
Manual. Calibrated Controller	183.80	9.05 x 10^5
RL-combined Controller	179.90	8.72 x 10^5

Compared to human driver and manually calibrated controller, **RL-combined control**:

- Obtains **3.54%** and **2.12%** decreasing in total travel time.
- Obtains **9.36%** and **3.65%** decreasing in total energy.

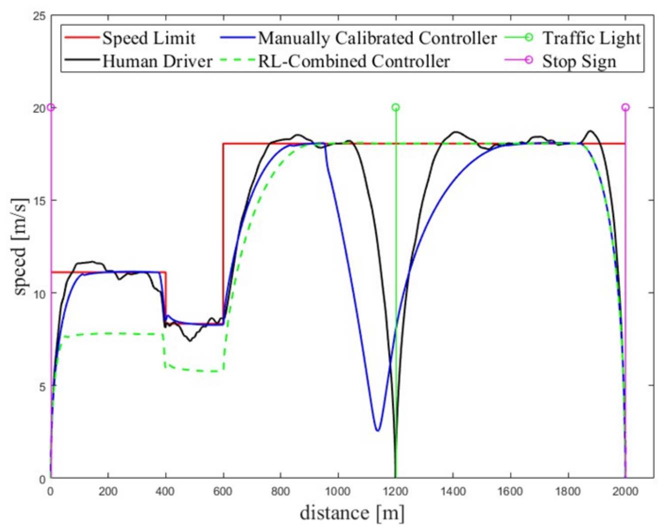

Figure I.1.1.2 RL-combined controller compared to human driver and manual-calibrated eco-driving controller.

Task 2: Evaluation, implementation, and validation of intelligent CAV controls

Demonstration and validation of ANL's optimizing eco-driving controls in a hybrid powertrain. In FY 2023, we validated ANL's "speed-only" optimizing eco-driving CAV control for the Hyundai Sonata Hybrid successfully. In collaboration with another EEMS project (XIL CORE 2), we performed the first full integration tests using a split architecture and "direct override" (without a robot driver) for the Hyundai Sonata hybrid electric vehicle (HEV) with the "speed-only" eco-driving control. Importantly, these tests revealed no functional errors for both single vehicle and multi-vehicle scenarios when employing AMBER's quality check process. In single-vehicle scenarios, we achieved up to 40% energy savings through a V2I eco-approach as shown in Figure I.1.1.3, using "adjusted fuel consumption" calculations, a necessary step to account for varying conditions of the hybrid electric system's battery. "Adjusted fuel consumption" was calculated by obtaining the energy conversion rate from the Δ state of charge (SOC) to fuel from each scenario using linear regression, and then calculating an average conversion rate from all scenarios, resulting in -3.037 g/%ΔSOC. Additionally, we validated our simulation model, RoadRunner, within 5% accuracy for most single-vehicle scenarios in terms of energy consumption. However, some scenarios exhibited up to a 35% variance in adjusted fuel consumptions, a challenge attributed to different initial SOC and Δ SOC in short-distance scenarios and a low number of repeats. As part of future work, we will improve the testing scenarios and procedures for HEV/plug-in hybrid electric vehicle (PHEV) to address this variability.

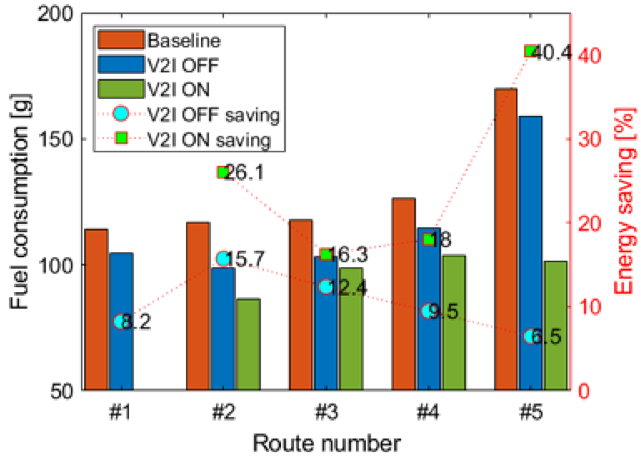

Figure I.1.1.3 Adjusted fuel consumption/savings for Hyundai Sonata Hybrid 2021 equipped with Argonne-developed eco-driving using direct override (acceleration), tested in lead position on five routes on dynamometer.

Demonstration and validation of a new eco-driving CAV control that co-optimizes speed and powertrain operations. Previous experimental work revolved around the "speed-only" control, which is a speed planner that is independent of vehicle type or powertrain. In FY 2024, we implemented the "powertrain+speed" eco-driving control, onto a conventional vehicle, the Chevrolet Blazer, demonstrating more than 5% energy savings compared to the "speed-only" control optimal control through 32 tests covering 84 miles (Figure I.1.1.4). This technology maintained all functionalities in 8 lead vehicle scenarios while adding just 3% more travel time and achieved an average 4.6% validation accuracy for the RoadRunner energy model. For this demonstration, we successfully implemented full powertrain control with direct override capabilities on the Chevrolet Blazer 2019, with control over the transmission through a unit programmed by GM, and longitudinal speed control by overriding axle torque demand and brake deceleration demand within the adaptive cruise control (ACC) module. The setup works well for highway scenarios, but despite GM's collaboration, presents some challenges, such as ACC disengagement at low-speed or excessive shifting times. Furthermore, we also demonstrated a novel human driver model, previously developed as part of a sister project, in the Blazer, marking a notable first in its application. In total, we conducted 132 tests, spanning approximately 343 miles, incorporating various controls, including "powertrain + speed" optimal control, for comparison and further demonstration.

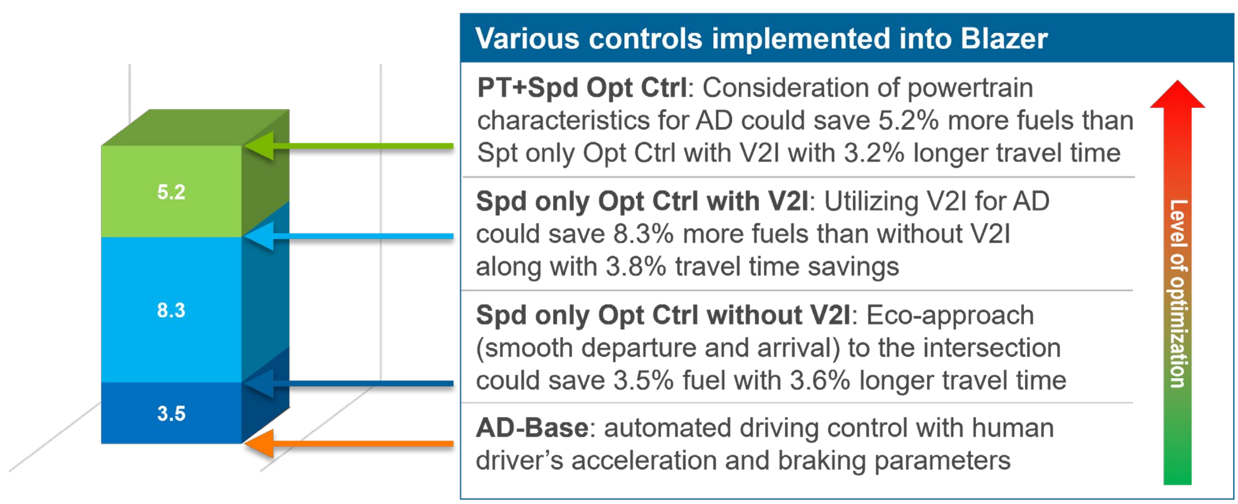

Figure I.1.1.4 Cumulative average fuel savings achieved at each new technology/control implementation in Chevrolet Blazer 2019.

An eco-motion planning and control system, jointly developed by Clemson and Argonne, demonstrated longitudinal and lateral motions of Clemson's CAV on the test track. We designed this system to enable energy-efficient driving with decision making capabilities in multi-lane scenarios. The functionality of this system was evaluated through track-based vehicle-in-the-loop (VIL) testing with Clemson's CAV across various lane-changing scenarios. The proposed eco-motion planning and control system has a hierarchical structure consisting of the following three modules:

1. Analytical long-term pacing, developed by ANL, provides energy-efficient driving capability by computing route-wide longitudinal trajectories.

2. Lane decision motion planner, developed by Clemson, provides obstacle avoidance capability by selecting a lane and computing target acceleration.

3. Low-level vehicle control, developed by Clemson, provides vehicle motion control capability with a focus on safety and driving comfort by computing throttle and steering control inputs.

We conducted a series of VIL tests to systematically validate the control system, including an open-loop lane change test that focused on motion tracking control, a free-road test that focused on lane change decision-making, and an urban corridor test that assessed the entire system. Figure I.1.1.5 shows the results of the urban corridor test with the presence of five virtual surrounding vehicles. The physical CAV smoothly changed lanes multiple times, leveraging the lane decision motion planner. These overtaking maneuvers minimized disruption from preceding vehicles to the analytical long-term pacing, improving energy efficiency and increasing traffic density in the urban corridor.

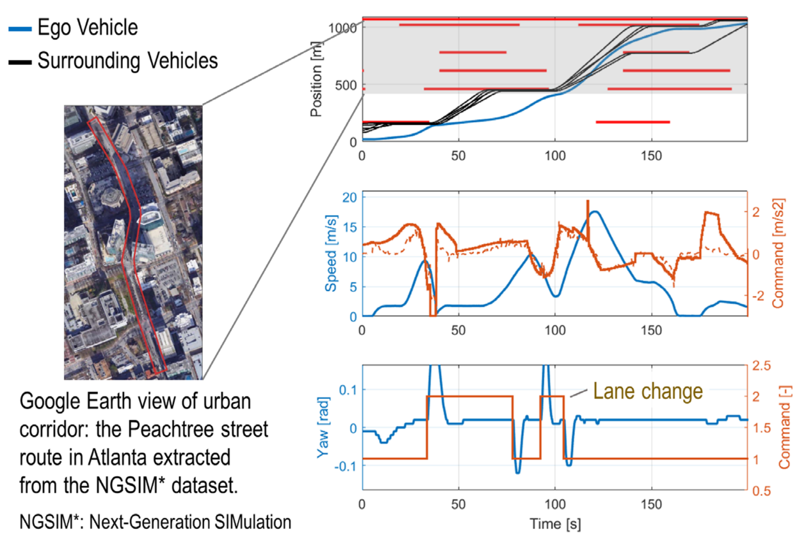

Figure I.1.1.5 Urban corridor test results: trajectories of position, speed, and yaw (on the left y-axis), as well as acceleration and lane decision commands (on the right y-axis). Horizontal red lines indicate the duration of the red-light interval.

An eco-speed advisory system (Eco-SAS) for human drivers was developed and demonstrated as a practical solution for connected vehicles. The Eco-SAS provides eco-speed suggestions to human drivers, computed using vehicle-to-infrastructure (V2I) information. It was improved and evaluated through a RoadRunner simulation study, and its effectiveness was experimentally demonstrated using a human-vehicle-in-the-loop platform, in which human drivers, wearing mixed reality (MR) goggles, responded to the eco-speed suggestions. For the simulation study, we modeled interactions between humans and the Eco-SAS to describe different levels of acceptance among human drivers, indicating how well they followed eco-speed suggestions. As shown Figure I.1.1-6, the simulation results found out that with a 70% Eco-SAS acceptance level, energy savings of up to 11% can be achieved, while a 90% Eco-SAS acceptance level can achieve near-optimal energy savings of up to 23%, close to CAVs. Even in traffic scenarios emulated using real-world datasets, where the impact of the Eco-SAS might be limited, it still contributes to large energy savings (e.g., up to 17% with a 90% Eco-SAS acceptance level).

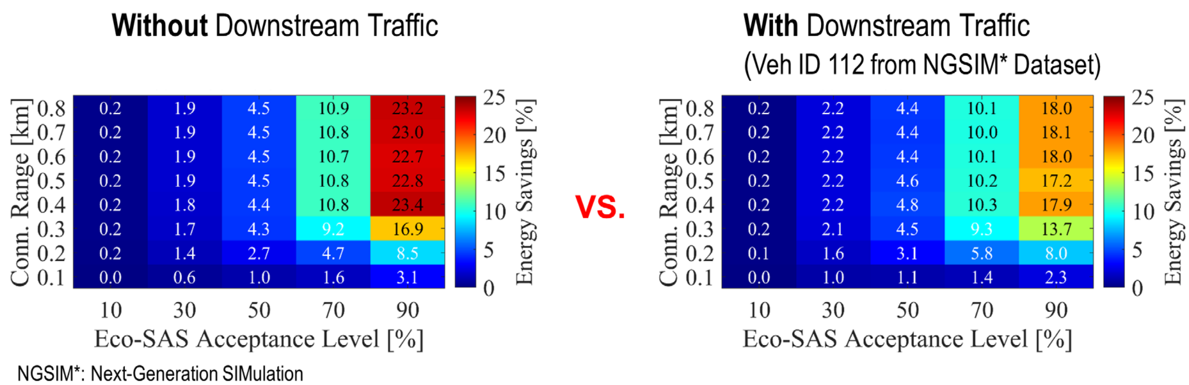

Figure I.1.1.6 RoadRunner simulation study results for the urban Peachtree corridor: energy-saving comparison between scenarios without and with downstream traffic. In the scenario with downstream traffic, an additional vehicle (Veh ID 112) was introduced in front of the simulated ego-vehicle.

A Level 3 CAV, featuring ANL's eco-speed planner, underwent functional testing under full-field test conditions. In preparation for full-field testing, ANL's eco-speed planner was integrated into University of Wisconsin's (UW's) Level 3 CAV system, ensuring smooth interaction with existing control layers. UW researchers demonstrated the functionality in a simple, low-speed scenario that included two traffic lights with cellular-vehicle-to-everything (C-V2X) technology for signal phase and timing (SPaT) broadcasting. UW's Level 3 CAVs are Lincoln MKZ hybrids equipped with a sensor suite, drive-by-wire control, and V2X communication powered by Autoware and CARMA. The integrated system was validated through several testing stages, including software-in-the-loop, hardware-in-the-loop, and full-field tests. During the full-field tests, two portable traffic lights were located at 50 m and 100 m to replicate the cellular-V2X connected and scaled-down corridor. The standard V2X messages, as defined by the J2735 protocol, were transmitted from roadside units (RSUs) to the onboard unit (OBU) of the CAV through direct V2X communication (PC5 mode), where both units were the Cohda Wireless MK6 model. As shown in the Figure I.1.1.7, the human driver came to full stop, while the CAV avoided this stop at the second traffic light. Additionally, CAV reduced its speed in advance and smoothly increased it, enabling it to enter the second traffic light during the next green phase under real-world conditions involving perception challenges and practical communication limitations.

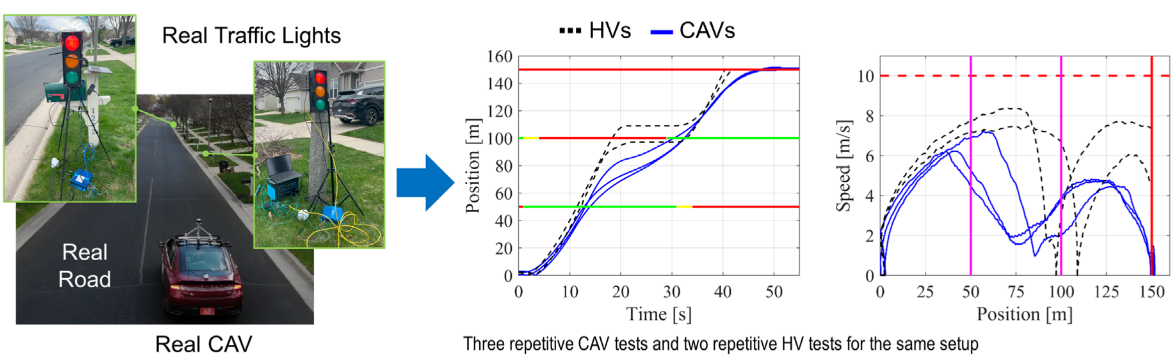

Figure I.1.1.7 Full-field test setup and results: trajectories of position (center) and speed (right). Horizontal green, yellow, and red lines (center) indicate the duration of each light interval, while vertical magenta and red lines (right) indicate traffic lights and stop signs, respectively.

Task 3: Methodology for real-world automation and connectivity energy benefits – a CRADA with GM

Real-world energy impacts of ACC using fleet-level data. In collaboration with GM, starting in July 2021, a large amount of data has been collected from their fleet of vehicles, including hundreds of signals related to vehicle dynamics (speed, yaw, etc.), powertrain (fuel rate, torque, rpm, temperature, etc.), accessory load (heating, ventilation, and air conditioning [HVAC] settings/operations), global position (GPS) coordinates, and ADAS sensors (e.g., gap with preceding vehicles). As of October 2023, key data summary statistics are: 54,551 trips, 1,343,935 km, 20,474 hours of driving, 161 vehicles, 70 vehicle models, 96 drivers with over 1.12 TB of data transferred. ANL has developed a robust pipeline to ingest, process, quality check, analyze, and visualize the data. This includes map-matching (adding attributes such as speed limit, grade, etc.), vehicle identification number decoding, as well as dashboards in Tableau. Leveraging this large amount of data, a multi-level, multi-resolution analysis has been conducted to understand the real-world energy impacts of connected and automated technologies:

- At a macro level, trips with and without ACC engagement were analyzed. Energy levels were aggregated and compared after statistical adjustments, removing known vehicle and driver biases and controlling for various driving and environmental factors. The results suggested that, all else being equal, a negative impact over the fleet (+0.26 L/100 km), equivalent to a 2% fuel penalty of engaging ACC (on average, across all vehicles, all drivers, all speeds etc.).

- At a segment level, trips were broken down into several driving modes (*Cruise, Brake and Acceleration, Brake Stop and Acceleration, Acceleration, Brake, Creeping*) and the benefit of ACC on energy was studied at a situation level. In this analysis, ACC led to greater fuel consumption in *cruising* mode (+0.14 L/100 km) and in *braking* mode (+0.33 L/100 km) when compared to no ACC usage in equal situations. ACC showed some benefit in transient modes: *break stop & accelerate*, *break & accelerate* and pure *acceleration* situations with an impact of respectively (-0.31 L/100 km) and (-0.27 L/100 km) and (-0.71 L/100 km) on overall fuel consumption (averaged over fleet). As cruising accounts for most of the driving in a given trip, this finding aligns with macro level results.

- At a driver level, we analyzed ACC could affect fuel consumption in different ways according to driving style (Figure I.1.1.8). Trip agnostic driver aggressiveness metrics were designed, clustering drivers into three groups of efficient, nominal and aggressive driver profiles. An energy analysis concluded that (1) for very calm drivers, engaging ACC led to sharp increase in fuel consumption ([+0.6, +1] L/100 km), (2) for average drivers, the ACC effect is slightly penalizing (+ 0.31 L/100 km), aligning with previous macro level results, (3) for aggressive and very aggressive drivers, engaging ACC actually led to fuel *savings* ([-0.2, -0.4] L/100 km).

- At a micro level, we designed an approach to model energy profile of individual trips correlating vehicle, and trip dynamics with second-by-second fuel consumption outcome while assuming dynamics are preserved (i.e., ACC engagement does not impact speed variation). In this setting, ACC system showed fuel benefits (-37 mL/sec ⇨ 1.6% improvement) suggesting some internal powertrain optimization or other benefits at operation level. This latest finding combined with previous analysis suggests that: while ACC appears to have an effect that goes beyond speed control taking advantage of predictability and potentially optimize engine operation or vehicle operation in general, it is generally worse at driving efficiently (worse speed control).

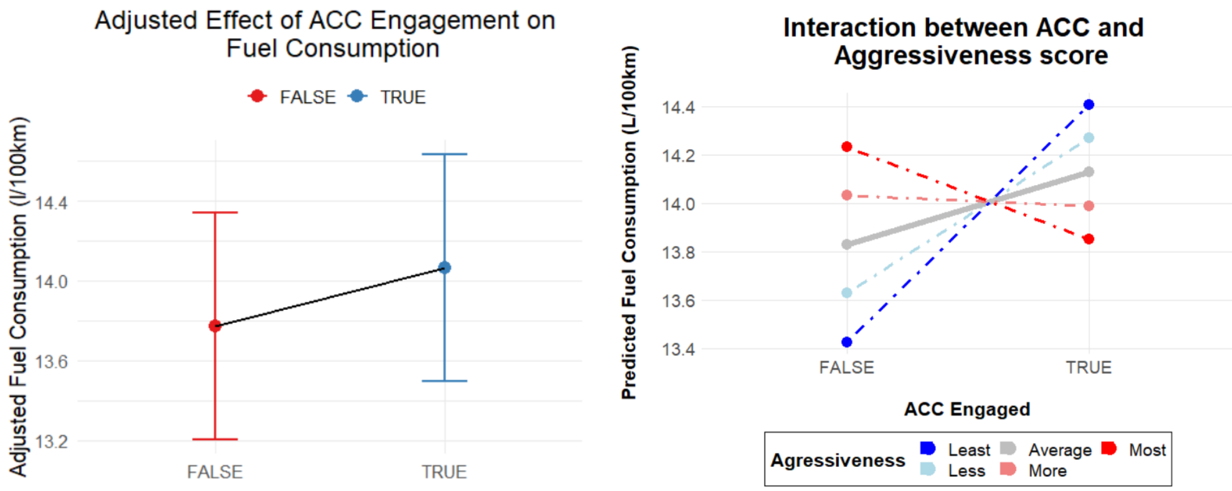

Figure I.1.1.8 Effect of ACC engagement on fuel consumption. Left: average effect after statistical adjustment via control of confounding variables. Right: average effect for drivers according to their aggressiveness, from least to most aggressive

In conclusion, current ACC systems may make internal powertrain operations more efficient, but they remain worse than the average driver at driving. This underscores the importance of personalized driving recommendations based on individual driving behavior as it might be beneficial for aggressive drivers to engage current ACC more often. On the research side, these results emphasize that energy-efficiency should be another objective of automated control development.

Methodology for generating representative scenarios for a given population. The energy effect of CAV technology is very scenario-dependent, and as a result, representative scenarios are critical in any methodology for energy impacts evaluation. We have developed a data-driven process to generate sets of "representative" scenarios of reasonable scale, yet retaining the statistical significance compared to the whole population. This will enable a manageable effort in simulation, in dynamometer-XIL, or in track experiments. The workflow is based on an unsupervised machine-learning technique (HDBSCAN – Hierarchical Density-Based Spatial Clustering of Applications with Noise), to detect the underlying grouping of similar trips throughout a geodemographic dataset; as a natural result of clustering, the trips with the highest membership strengths are selected as representative scenarios. The originality of the workflow lies in the feature engineering step that casts the data points using energy consumption-focused similarity metrics. The workflow was first applied to the Chicago metro population, with input data a random subset of ~200k trips from POLARIS simulations. The workflow yielded six groups of representative trips, as shown in Figure I.1.1.9

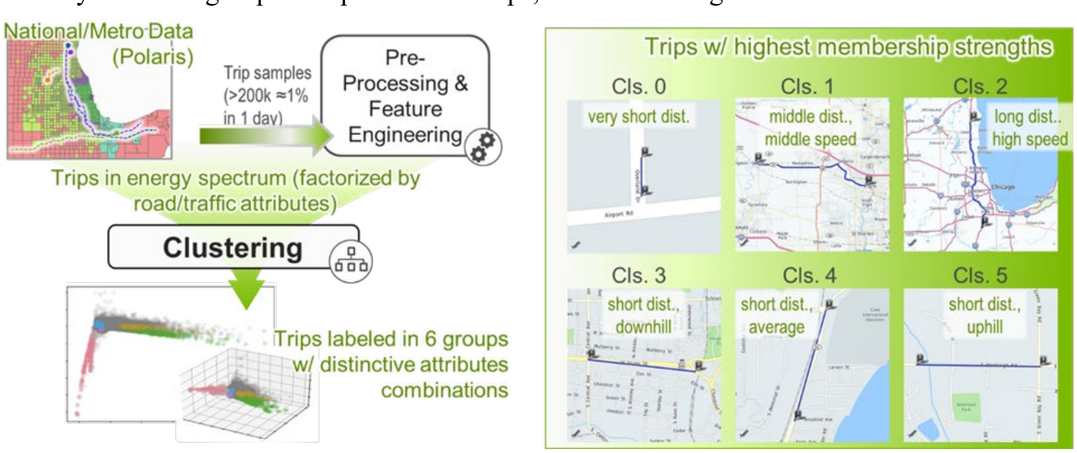

Figure I.1.1.9 Data-driven workflow of scenario generation is applied to POLARIS data of random trips and results in six distinctive clusters. Trips with the highest membership strengths are selected as representative scenarios.

Conclusions

This project aims to develop energy-saving eco-driving controls for CAVs, quantify their energy benefits under a variety of conditions, demonstrate them in real vehicles, and define methodologies and metrics for real-world energy impacts. In the second year of a planned three-year project, we made major inroads towards these goals. Key achievements include:

- Application of RL to achieve better performance of eco-driving controllers, demonstrating a workflow for training and application on a simple scenario, that will be scaled-up and evaluated in early FY 2024.
- Demonstration and validation of Argonne's optimizing eco-driving controls in a hybrid powertrain. This first application to hybrids confirmed fuel savings can still be achieved for advanced powertrain, but also highlighted the need for longer scenarios, especially for hybrids.
- Demonstration and validation of a new eco-driving CAV control that co-optimizes speed and powertrain operations. Working with CRADA partner, GM, we achieved controllability of speed and powertrain in certain operating domain on the dynamometer, which we then leveraged to apply for the first time an algorithm that co-optimizes the powertrain at the same time as the speed.
- Development and on-track demonstration of CAV controls that feature both longitudinal and lateral motions of Clemson; experiments emulated a real-world, multi-lane corridor.
- Demonstration of an eco-speed advisory system for human drivers of connected vehicles, where drivers can follow speed advisory displayed on see-through MR goggles. Such a system can bring energy savings, even without full acceptance by end-users.
- Functionality demonstration of Level 3 CAV with eco-driving controls in experiments also featuring C-V2X traffic signals; large-scale experiments to be conducted in early FY 2024.
- Evaluation of real-world energy impacts of ACC using fleet-level data, at various scales, showing that ACC as implemented today may lead to greater energy consumption, though it can prove beneficial for aggressive drivers.
- Development of a methodology for generating representative scenarios, which will be used in a proposed method for evaluating the energy impacts of CAVs.

Key Publications

All manuscripts available at vms.taps.anl.gov/publications

1. T. Ard, L. Guo, J. Han, Y. Jia, A. Vahidi, and D. Karbowski, "Energy-Efficient Driving in Connected Corridors Via Minimum Principle Control: Vehicle-in-The-Loop Experimental Verification in Mixed Fleets," IEEE Transactions on Intelligent Vehicles, vol. 8, no. 2, pp. 1279–1291, 2023, doi: 10.1109/TIV.2023.3234261.
2. J. Han et al., "Energy Impact of Connecting Multiple Signalized Intersections to Energy-Efficient Driving: Simulation and Experimental Results," IEEE Control Systems Letters, vol. 7, pp. 1297–1302, 2023, doi: 10.1109/LCSYS.2023.3234808.
3. J. Jeong, A. Dudekula, E. Kandaswamy, D. Karbowski, et al., "On-Track Demonstration of Automated Eco-Driving Control for an Electric Vehicle," SAE Technical Paper 2023-01-0221, 2023, doi: 10.4271/2023-01-0221.

4. J. Han, T. Ard, R. Wang, P. Gupta, A. Vahidi, Y. Jia, and D. Karbowski, “Human driver interaction with an eco-speed advisory system in connected vehicles: simulation and experimental results,” the 2024 TRB 103rd annual meeting (*accepted*), Washington, D.C., 2024.

5. Gupta, Shobhit, Daliang Shen, Dominik Karbowski, and Aymeric Rousseau. “Koopman Model Predictive Control for Eco-Driving of Automated Vehicles.” In *2022 American Control Conference (ACC)*. Atlanta, GA, USA: IEEE, 2022.

6. Han, Jihun, Woong Lee, Dominik Karbowski, Aymeric Rousseau, and Namwook Kim. “Fine-Tuning a Real-Time Speed Planner for Eco-Driving of Connected and Automated Vehicles.” In *IEEE Vehicular Power and Propulsion Conference (VPPC) 2020*. Gijón, Spain, 2020.

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I.1.2 Energy-Efficient Connected and Automated Vehicle Models and Workflows (Argonne National Laboratory)

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Start Date: October 1, 2020 End Date: September 30, 2023
Project Funding: $3,500,000 DOE share: $3,500,000 Non-DOE share: $0

Project Introduction

A mobility system is made of many subsystems including travelers, infrastructure and vehicles. The energy efficiency of such a complex system depends on the performance of each sub-system, as well as on the interactions between them. Simulation tools are essential for research on these mobility systems; they help guide analysis of existing and future scenarios and technologies and are essential to identify levers for greater energy-efficiency. The ANL-led SMART Mobility workflow, initiated in SMART 1.0 is a set of interconnected tools and processes that help support such research. This project focuses on the part of this workflow centered around vehicles and their drivers.

Vehicles are the machines directly consuming energy in a mobility system. Detailed modeling of how they operate and spend energy is therefore critical for accurate energy impact calculations, especially of new technologies such as driving automation or connectivity and is necessary for "vehicle-centric" optimization. RoadRunner and SVTrip (Stochastic Vehicle Trip Profile) are two tools that help in that regard, and this project concentrates on the development and deployment of these tools.

RoadRunner has been instrumental in SMART 1.0 in enabling the development and evaluation of advanced CAVs controls, with a focus on energy. It helps researchers and engineers develop energy saving algorithms that rely on a combination of powertrain controls, driving automation, connectivity, and sensing. It can simulate multiple connected and automated vehicles with full powertrain models as well as the interactions between vehicles and their environment. RoadRunner uses powertrain models from Autonomie, an established state-of-the-art vehicle energy-consumption simulator developed with U.S. DOE support, and adds new capabilities, such as multi-vehicle simulation, models of road characteristics, causal models of human driving, V2X communications, and sensors.

SVTRIP is a data-driven software tool developed at Argonne that generates ≥1 Hz naturalistic vehicle speed profiles following training on large datasets of recorded driving data. Several use cases associated with the SMART workflow are possible.

Objectives

In this project, the main objective is to further develop RoadRunner and SVTrip to make them better and easier to use, in direct support of SMART Mobility research conducted by ANL (within the "Development and Validation of Intelligent CAV Controls for Energy-Efficiency" project), and for external users of these tools. Both tools will be publicly released over the course of this project. The developments include more advanced models, professional user interfaces, and new ways (or workflows) of using the tools in combination of other tools and processes.

One novel workflow is the XIL workflow. XIL implies an experiment that combines real hardware and virtual simulated systems with close-loop interactions between them. As an evolution to existing “component-in-the-loop” approaches, XIL is tailored for connected and automated vehicles, where the type of real system is not necessarily fixed—e.g., a traffic light can be real or virtual. The XIL workflow links together RoadRunner and Argonne’s dynamometer-based facilities and experimental vehicles, thus adding a unique hardware component to the SMART mobility workflow.

The approach combines work on developing better tools and workflows in Task 1 and adding new models to the tools in Task 2.

Approach

Task 1: Tools and workflows

As part of this three-year project, a new RoadRunner version release is delivered yearly, with new features, new models and new interfaces. Each release is thoroughly tested thanks to the integration of RoadRunner into a professional software life-cycle process, ensuring a robust and predictable experience for the user. RoadRunner will be integrated with the advanced model-based engineering resource (AMBER) and other ANL tools, such as Autonomie or SVTrip. The new interactive simulation result visualizer enables easier and faster analysis of complex, multi-vehicle results.

New workflows are also added to expand the RoadRunner use cases beyond its more typical use case. One new workflow is the integration with traffic models, to enable more accurate simulation of CAVs since surrounding traffic has a major impact on the movement of a vehicle, and proposed CAV controls have to be effective under a variety of traffic conditions. This is done through integration of dedicated micro-simulation tools such as Simulation of Urban MObility (SUMO), and through direct integration of traffic proxies, such as SVTrip, into the RoadRunner framework. Another workflow is automated CAV controls calibration, i.e., a workflow to find the “best” values for a set of control parameters that result in the minimum energy consumption, or in a minimum of a user-defined trade-off function.

The new XIL workflow expands the use of RoadRunner into hardware experimentation. The XIL workflow enables efficient and streamlined testing of energy-focused CAV controls in a setup that combines hardware and simulated systems—e.g., an actual vehicle on a dynamometer, with virtual road and surrounding vehicles. The XIL framework inherits many of RoadRunner’s features: an environment simulation with the right level of complexity/fidelity for energy-focused CAV research, a library of CAV-related vehicle models, the ability to quickly define scenarios that include road infrastructure and other vehicles, etc. Thanks to shared components with AMBER and Autonomie, RoadRunner will also add to the XIL framework: workflow management, easy linkages to third party tools, file/model/result organization system, and a professional interface.

Task 2: Models

New models and scenarios expand the range of technologies and situations that can be simulated in RoadRunner. This includes models of V2X communications, sensors, lateral dynamics, as well as models of existing automated vehicles and the underlying automated driving controls.

Results

Task 1: Workflows

2024 RoadRunner Release. In FY 2023, the team released a new version of Roadrunner along with the AMBER 2024 release. RoadRunner 2024 includes the ability to edit parameters and calibration files, along with building, evaluating and generating reports for individual agents. There were also numerous backend improvements to the architecture building and management. These improvements will allow revised architectures in the future to assist in XIL work. A figure of the user interface (UI) for editing agents and their parameters and calibration files is shown in Figure I.1.2.1.

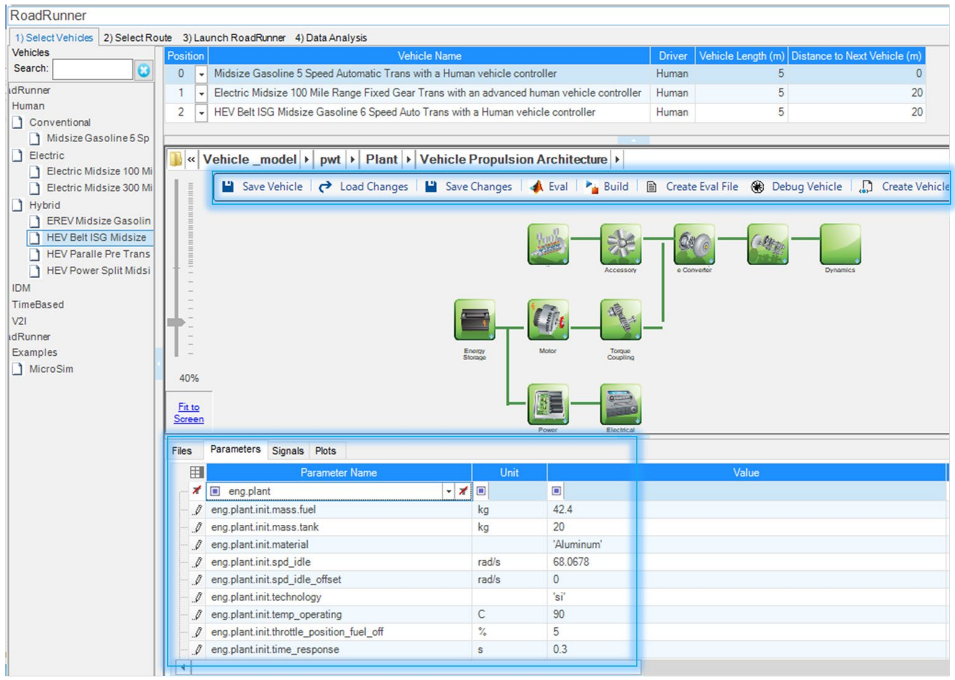

Figure I.1.2.1 New RoadRunner user interface for editing agents

Users have also requested the ability to queue simulation runs so that a study can be performed entirely through the RoadRunner UI. To address this requirement, a queuing feature was added to RoadRunner. This allows users to modify either the platoon or the route and then queue that run and subsequently create another platoon and route combination.

A proof-of-concept for AI-enabled control parameter optimization was developed and tested using a sample dataset. By leveraging machine learning techniques, this AI-enabled control parameter calibration process reduced computational costs while optimizing control parameters for eco-driving controllers in connected and automated vehicles that satisfy desired performance metrics. As shown in Figure I.1.2.2, this process requires initial simulation runs using predefined parameter sets, and the resulting data points are then mapped into the metric space. Deep learning networks can be trained to identify a data-driven relationship using parameters sets and their corresponding metric sets. At the stage of the parameter space exploration, the Pareto frontier can be identified in the metric space, where the desired metric point is defined. If there are not enough data points near the desired metric point, additional simulations can be designed based on new parameter sets, which are inversely searched using metric sets defined within the new search region; otherwise, the parameter set corresponding to the desired metric set is considered as the outcome of the process. We also considered two different approaches for inversely searching parameter set for a given metric set: 1) an iterative approach using a trained surrogate “forward” machine learning (ML) model (with input as the parameter set and output as the metric set) with global optimization methods, and 2) a direct approach using a trained surrogate “inverse” ML model (with input as the metric set and output as the parameter set). Both approaches generated the parameter sets for the given metric sets. Through actual simulations, it was verified that the metric sets obtained from these parameter sets matched the originally given metric sets.

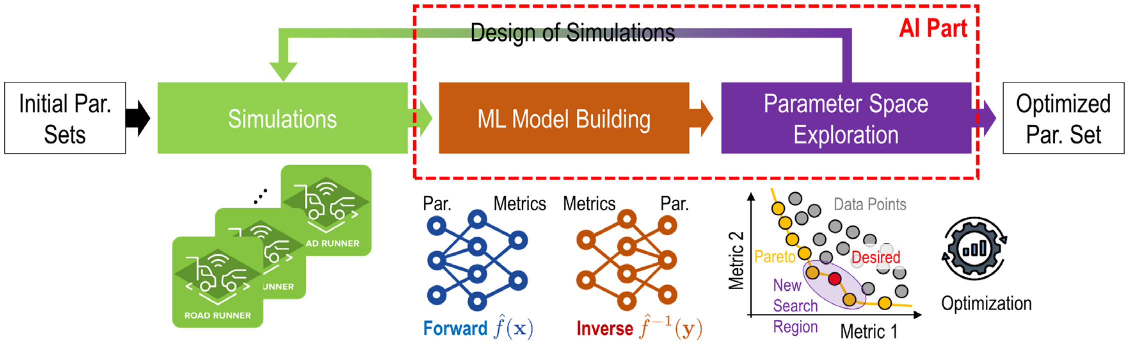

Figure I.1.2.2 Workflow for AI-enabled calibration of control parameters

Integration of traffic models with RoadRunner. We fully automated the linkage between RoadRunner and the traffic flow micro-simulation tool SUMO and integrated this linkage into AMBER platform as a release-ready workflow. As shown in Figure I.1.2.3, SUMO serves as the traffic-scale simulation backbone and defines the simulation environment, while RoadRunner takes over behavior of some of the vehicles running in the environment. SUMO defines the road network, traffic lights, road signs and traffic vehicles. The driving control of vehicles designated by users is performed in RoadRunner using high-fidelity vehicle models. This RoadRunner co-simulation workflow programmatically generates the models needed and conducts a co-simulation instance with the scenario defined by the user. The co-simulation runs RoadRunner and SUMO simulations simultaneously, where both tools communicate with each other and accomplish the simulation in a common traffic environment. The linkage is supported by SUMO examples of different mobility scales as well as a SUMO scenario generation pipeline. Three co-simulation use cases—synthetic route, Chicago urban corridor, Lemont local network— were demonstrated.

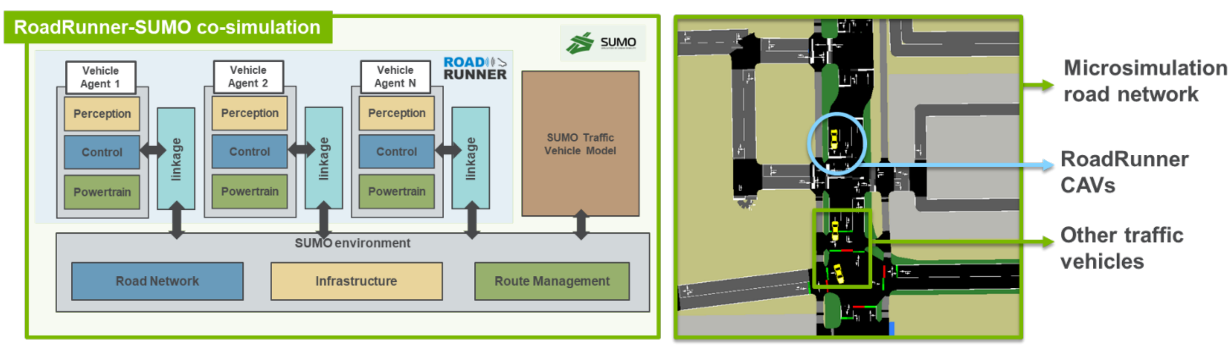

Figure I.1.2.3 Framework of RoadRunner-SUMO co-simulation

RoadRunner Visualizer. The RoadRunner Visualizer provides a view of the simulated vehicles as seen from above. We further improved the robustness, suitability, and functionality of the RoadRunner Visualizer. As is shown in Figure I.1.2.4, the visualizer can be launched from the AMBER graphical user interface (GUI) with a single click and can help users monitor RoadRunner simulation results by visualizing signals in vivid two-dimensional (2D) top-view animation and in user-interactive dynamic plots synchronously. New features of the visualizer were added and include results comparison between multiple simulations in dynamic graphs, Command Line Interface, refinement of the integration of animation and dynamic signal plotting that makes the visualizer more stable and portable for release, etc. AMBER capability was also improved such as enhancing the capability to load Anaconda/Python virtual environment on the local machine, allowing users to setup the virtual environments within AMBER GUI. The step-by-step user guide of this visualizer is provided along with the RoadRunner release document, including instructions about installing, running, main features of this visualizer as well as instructions of other use cases as the special design for real-time visualization, real-world data investigation, etc.

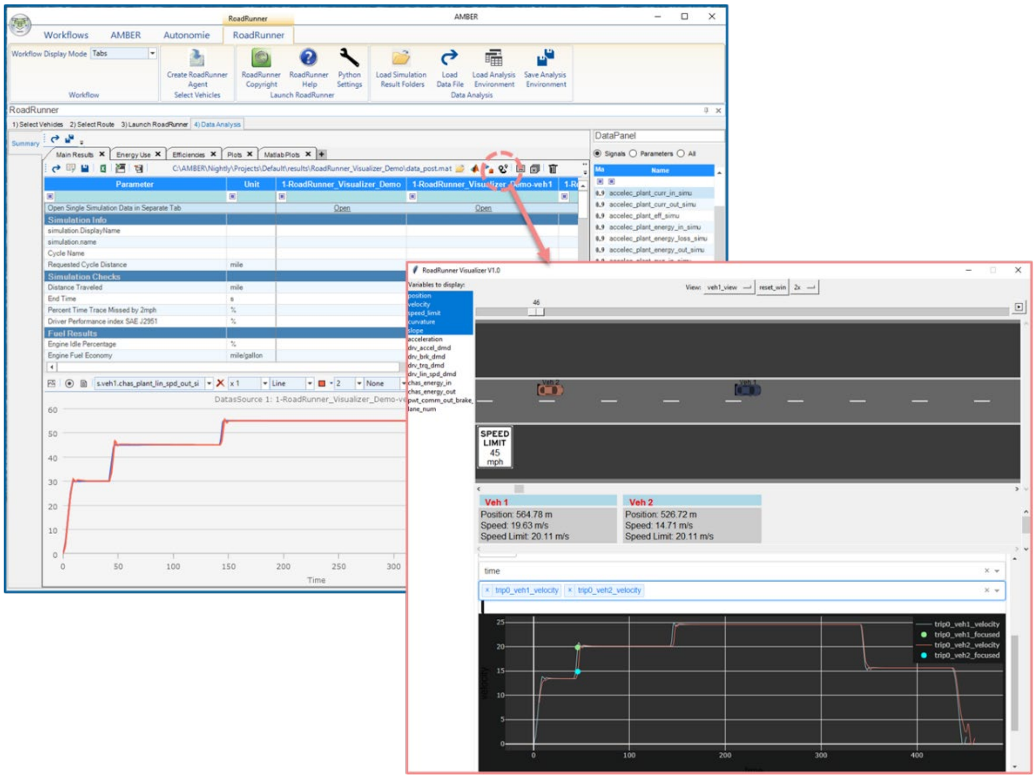

Figure I.1.2.4 RoadRunner visualizer integrated into AMBER GUI

Advancing ANL XIL Workflow Capabilities. The XIL workflow enables fast, robust, and repeatable testing of CAV controls and systems combining real hardware and virtual systems. Throughout FY 2023, ANL's XIL workflow has undergone various enhancements and expansions (see Figure I.1.2.5). These improvements were prominently showcased in multiple testing campaigns for ANL's new eco-driving controls in the Chevrolet Blazer and Hyundai Sonata hybrid, utilizing direct override. Our team integrated a split architecture and direct override seamlessly into the RoadRunner automated building process in the XIL workflow. This integration streamlined automated signal recording, diagnostics, and enhanced monitoring. The introduction of direct override facilitates "by-wire" control of the vehicle, eliminating the need for a robotic driver and significantly reducing preparation time for driver tuning. In addition, we've developed a flexible model-building process within RoadRunner to strengthen the capability of XIL workflow, supporting the Cooperative Driving Automation (CDA) project. This process will allow the demonstration of control and hardware communication which requires a novel RoadRunner architecture for new types of experiments. We've also incorporated dynamic aero load adjustments, grounded in testing data, to accommodate varying distances between multiple vehicles. This collaborative effort extends to our partner project, XIL CORE 2. The XIL workflow's newfound flexibility and efficiency expand its potential for future demonstrations. It will prove instrumental in projects such as CDA, ENACTED, and ADVANCE (freight-in-the-loop).

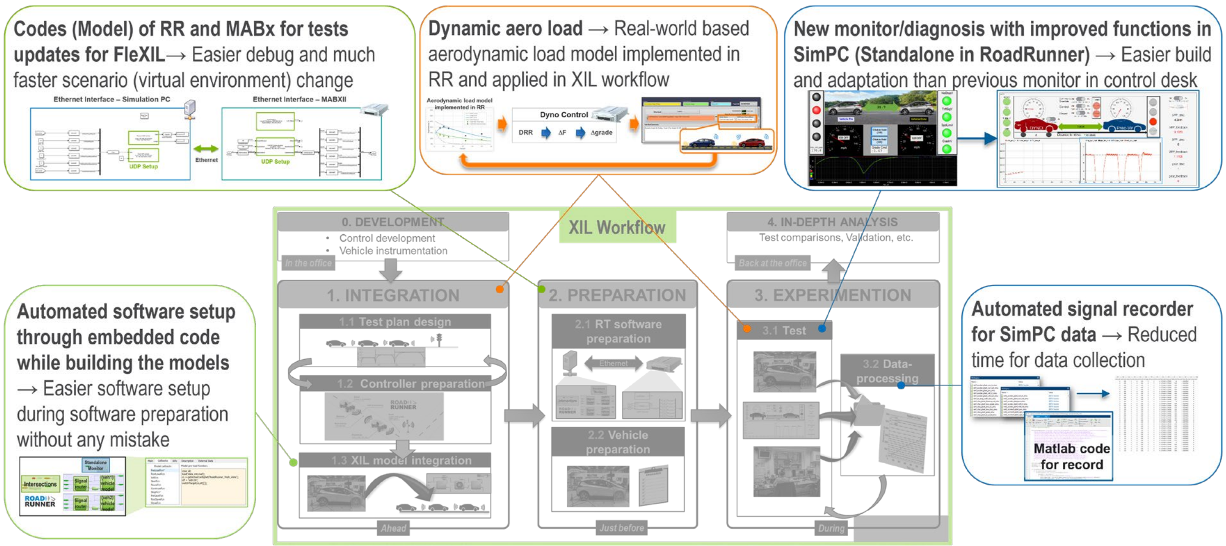

Figure I.1.2.5 Improvements and new features added to the XIL workflow process

A mixed reality tool (MRT) was developed and demonstrated in on-track human-vehicle-in-the-loop (H-VIL) tests. Clemson University developed the MRT, enabling human drivers to interact with virtual objects in simulated traffic scenarios. Realism was improved to make human drivers feel more immersed when performing H-VIL tests. To this end, we conducted two types of H-VIL tests: route-based and drive cycle-based tests that focused on interaction with virtual traffic signs and moving vehicles, respectively. The key components of the on-track H-VIL test platform include physical instrumented vehicles and a test track, human drivers, a mixed reality device with see-through displays, offboard and onboard computing, and microsimulation. Figure I.1.2.6 shows how these components are connected and interact with each other. The on-track H-VIL test platform was used to generate human-driven vehicle case (baseline) for an apples-to-apples comparison with CAV cases, as well as to evaluate the feasibility of an Eco-SAS for human drivers. We confirmed that the driving behaviors of human drivers were improved when they used the Eco-SAS while driving Clemson's CAV in a virtual urban corridor.

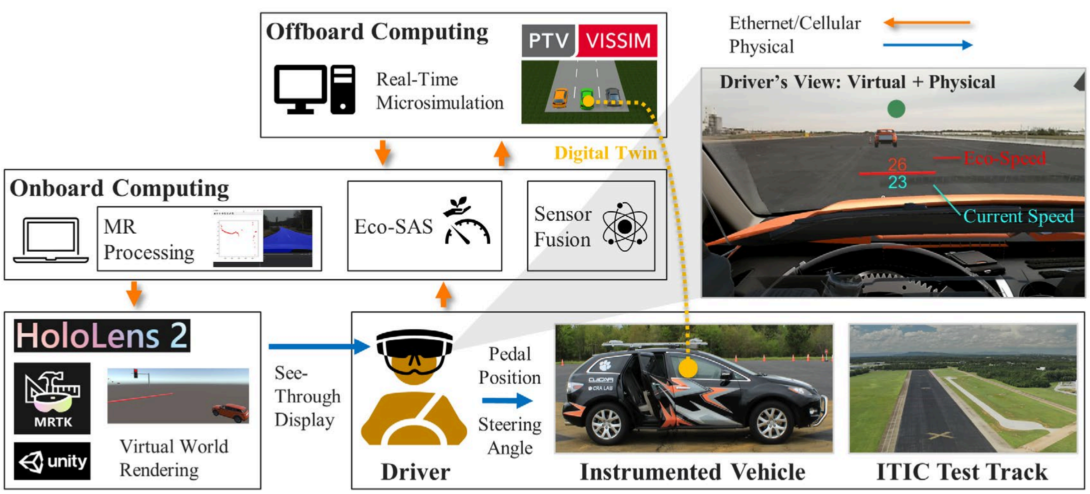

Figure I.1.2.6 Overview of the on-road H-VIL testing platform

Model validation of existing automated driving system. As an increasing number of automated driving systems emerges on the road, it is important to validate current state-of-art automated driving systems to learn their energy impacts and establish a realistic baseline for advanced eco-driving control. Thus, we are using real-world test-driving data collected by ANL (PI: M. Duoba) to validate ACC models in various driving scenarios. The validation of CT6 ACC model was carried out in FY 2022, and in FY 2023 we made system improvement by developing RoadRunner structure that imitates real-world preceding vehicles by a dummy model and features warming ramp for the random initial status of segmented driving trips. The simulation workflow was also improved to facilitate large-scale validation in RoadRunner, where a large amount of segmented real-world trips is replicated in RoadRunner simulations. Similar work on the Tesla Model 3 Autopilot ACC model validation will be completed in early FY24 – this will leverage both urban and highway driving data, including 1,213 miles driven and 61 test trips.

A high-fidelity human driver model was developed and validated using a large volume of Hyundai customer driving data. The high-fidelity human driver model features a novel architecture consisting of a perception and decision (PnD) model, as well as an action model. As shown in Figure I.1.2.7, we developed and validated the model through an established modeling process consisting of three main steps as follows.

- Module development and validation: all essential modules for each model were developed through data processing and preparation, data-driven and analytical modeling, and parameter extraction. For example, regression models were developed for the parameter update module within the PnD model, while mathematical models were developed for the drivability-oriented speed generation module within the action model. These modules were validated at the driving regime level (e.g., acceleration regime).
- Model development and implementation: all modules were integrated to build the entire human driver model, ensuring interactions among them. The developed model was implemented in RoadRunner, enabling it to use information about surrounding environments and generate realistic driving behaviors during simulations. Furthermore, a realistic range for the key parameters of the driver model, extracted from data, was added to assist users in configuring realistic settings for introducing heterogeneity among human-driven vehicles in simulations.
- Model evaluation and validation: the model's maturity was improved through extensive testing involving various trip-based scenarios with combinations of key parameters, leveraging parallel computing capabilities. At the trip level (traveling from origin to destination), we confirmed that the simulated data closely matched the real driving data characteristics.

We deployed RoadRunner with new human driver model at partner OEM for powertrain control development and provided support for model usage, refinement, and improvement.

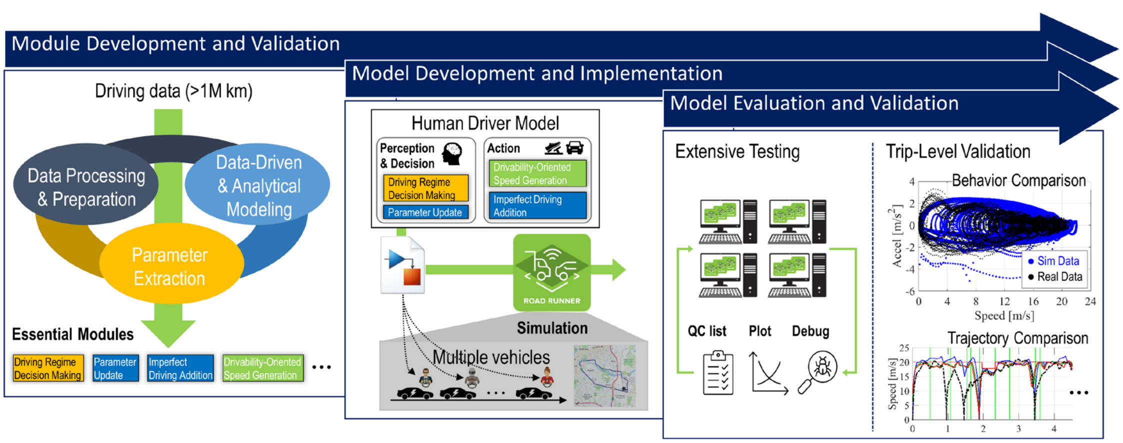

Figure I.1.2.7 An overview of the established modeling process for human driver models

SVTrip-AI. Partner George Mason University has explored several approaches for stochastic vehicle trajectory generation (SVTrip). SVTrip is an important aspect of aspect of workflow used by Argonne's modeling group for estimating fuel consumption and automation technologies. First, we developed a sampling algorithm that could generate realistic trajectories by splitting a trip into "micro-episodes." Each micro-trajectory can be approximated by a linear (acceleration/deceleration) or quadratics function (change from acceleration to deceleration). We have developed filtering algorithms for finding the points at which the shifts happen between three regimes: acceleration deceleration, cruising. Further, we have developed a probabilistic model for duration of the episode variable. Thus, each episode is parametrized by (duration, slope, quadratic term). Thus, we model the speed trajectory as a Markov decision process with a three-dimensional state. We use speed trajectory data collected from GPS sensors at 1 second interval for training and validating our models. There are 1.9 million data points in the training sets, with the trip lengths varying between 100 and 6,330 seconds. The dataset includes multiple trips with different lengths and starting and ending points. Results for an example trip are shown in Figure I.1.2.8.

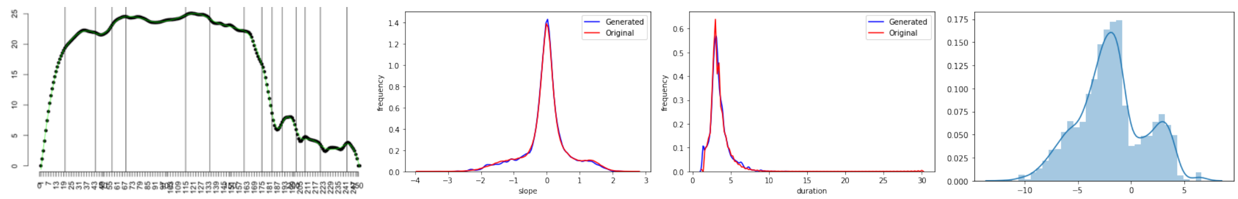

Figure I.1.2.8 Results from new SVTrip algorithm: [Left] Segmentation into parabolic segments. [Center-left]. Distribution of speed curve slopes (fitted vs observed). [Center-right]. Distribution of duration (fitted vs observed). [Right]. Distribution of speed from observed trips and from generated ones.

Conclusion

This project aims to expand the capability of tools and models used to conduct research into energy-efficient CAVs and future mobility, with a focus at the vehicle-level. The developments revolve mostly around RoadRunner, Argonne's simulation tool for energy-efficient CAV controls development.
Key achievements for FY 2023 include:

- 2024 RoadRunner Release, with better ability to edit parameters and calibration files, report generation for individual agents, revised architectures, and an interface to queue simulation runs.
- AI-enabled control parameter optimizer, which accelerates the calibration of CAV eco-driving controls.
- Full automation of the linkage between RoadRunner, and integration into the public release.
- Improvements in robustness and functionality of the RoadRunner road-view visualizer.
- Improvements in the Argonne's XIL workflow, enabling testing with direct override and with new powertrain (hybrid).
- Completion and deployment to industry partner of new human driver model
- Promising developments for the AI version of SVTrip.

In FY 2024, we will complete model validation of the Tesla Autopilot, as well as complete the development of SVTrip-AI.

Key Publications

All manuscripts available at vms.taps.anl.gov/publications

1. Behnia, Farnaz, Karbowski, Dominik, and Sokolov, Vadim "Deep Generative Models for Vehicle Speed Trajectories", *Appl Stochastic Models Bus Ind*. 2023; 39(5): 701-719. doi: 10.1002/asmb.2816

2. Gupta Prakhar, Rongyao Wang, Tyler Ard, Jihun Han, Dominik Karbowski, Ardalan Vahidi, and Yunyi Jia, "An X-in-the-Loop (XIL) Testing Framework for Validation of Connected and Autonomous Vehicles," accepted for presentation at IEEE International Automated Vehicle Validation Conference 2023, Austin, TX, USA, 2023

3. Han, Jihun, Woong Lee, Dominik Karbowski, Aymeric Rousseau, and Namwook Kim. "Fine-Tuning a Real-Time Speed Planner for Eco-Driving of Connected and Automated Vehicles." In *IEEE Vehicular Power and Propulsion Conference (VPPC) 2020*. Gijón, Spain, 2020.

4. Han, Jihun, Daliang Shen, Dominik Karbowski, and Aymeric Rousseau. "Leveraging Multiple Connected Traffic Light Signals in an Energy-Efficient Speed Planner." *IEEE Control Systems Letters* 5, no. 6 (December 28, 2020): 2078–83.

5. Han, Jihun, D. Karbowski, and A. Rousseau, "Analytical Anticipative Optimal Drivability Car-Following Model," in 2022 American Control Conference (ACC), Atlanta, GA, USA, Jun. 2022.

6. Han, Jihun, T. Ard, R. Wang, P. Gupta, A. Vahidi, Y. Jia, and D. Karbowski, "Human driver interaction with an eco-speed advisory system in connected vehicles: simulation and experimental results," the 2024 TRB 103rd annual meeting (accepted), Washington, D.C., 2024.

7. Hyeon, Eunjeong, Jihun Han, Daliang Shen, Dominik Karbowski, Namwook Kim, and Aymeric Rousseau. "V2V Enhanced Eco-Driving: Impacts on Its Energy Saving Potential." In *10th IFAC International Symposium on Advances in Automotive Control (in Review)*. Columbus, OH, USA, 2022.

8. Hyeon, Eunjeong, Daliang Shen, Dominik Karbowski, and Aymeric Rousseau. "Forecasting Short to Mid-Length Speed Trajectories of Preceding Vehicle Using V2X Connectivity for Eco-Driving of Electric Vehicles." Detroit, MI, USA: SAE International, 2021.

9. Jeong, Jongryeol, Namdoo Kim, Miriam Di Russo, Jihun Han, Dominik Karbowski, Kevin Stutenberg, and Julien Grave. "Vehicle-in-the-Loop Workflow for the Evaluation of Energy-Efficient Automated Driving Controls in Real Vehicles." In *SAE Technical Paper 2022-01-0420*. SAE International, 2022.

10. Zhang, Yaozhong, Jihun Han, Namdoo Kim, and Dominik Karbowski. "Model Validation of Adaptive Cruise Control in Vehicles Utilizing Real-world Driving Data." In *IEEE International Automated Vehicle Validation Conference (IAVVC) 2023*. Austin, TX, USA, 2023.

Acknowledgements

Argonne researchers: Phil Sharer, Namdoo Kim, Yaozhong Zhang, Jihun Han, Jongryeol Jeong, Daliang Shen, Eunjeong Hyeon, Aymeric Rousseau.

University project partners: Tyler Ard, Ardalan Vahidi, Longxiang Guo, Rongyao Wang, Yunyi Jia, Prakhar Gupta (Clemson University), Vadim Sokolov, Farnaz Behnia (George Mason University).

I.1.3 SMART 2.0 Transportation System (Argonne National Laboratory)

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Start Date: October 1, 2022 End Date: September 30, 2023
Project Funding: $3,470,000 DOE share: $3,470,000 Non-DOE share: $0

Project Introduction

The SMART 1.0 research portfolio addressed numerous research questions relating to energy, mobility, and productivity impacts of future transportation technologies, including private and shared AVs, e-commerce delivery, growing ride hailing, transit, and more. However, previous research did not adequately address several transportation trends that are expected to have major implications for energy and mobility (e.g., freight electrification, last mile delivery, passenger micro-mobility, curb management). Similarly, numerous critical inputs (value of time, connectivity, etc.) primarily relied on assumptions rather than data-driven models of future behavior.

The project seeks to move the state-of-the-art by extending the workflow to cover issues around:

- V2X connectivity
- Vehicle automation
- Infrastructure management (e.g., intelligent transportation systems [ITS], traffic signal coordination)
- Transit route and schedule optimization, on-demand and micro-transit and rideshare-transit integration.
- Parking and curb space management
- Eco-approach/departure/routing and other control strategies
- Freight management and optimization under connectivity, automation, and a changing demand environment
- Deployment and validation of SMART Mobility technologies

To capture complex interactions between systems and models, each task requires fundamental research across several fields, including behavior modeling, system optimization, vehicle control, and infrastructure technologies. As an example, when considering ride hailing and ride pooling optimization, one needs to simultaneously consider the potential increase in mode share along with the impacts on traffic flow and curb management, as well as land use change. In addition, the workflow extension will require connection with new tools and models. Using the new automated processes, the extended capabilities will allow us to significantly expand our understanding of the impact of new transportation technologies.

Several diverse new technologies have disrupted transportation as we know it and are expected to continue to do so in the near future. Their long-term impact and interactions with existing systems remain largely unknown. As a result, both public (e.g., urban planners, cities) and private (e.g., automotive, mobility, suppliers) organizations face uncertainties when committing to long term investments and adopting solutions.

Objectives

The primary objective of this project is to use the SMART Mobility Workflow (POLARIS/SVTrip / Autonomie/UrbanSim /MEP) to quantify the impacts of numerous mobility technology disruptions and behavioral changes on transportation energy, mobility and productivity using the unique integrated systems-level approach implemented in the POLARIS-centered SMART Mobility Workflow. This project seeks to quantify the impact of individual modes, technologies, and management strategies (e.g., connectivity, new modes, freight, electrification, land use...) as well as how they collectively affect the entire transportation system.

Approach

The SMART Mobility modeling workflow previously developed linked a series of simulation tools including land use, travel behavior, activity-modeling, traffic flow, microsimulation, energy consumption, electric vehicle supply equipment (EVSE) siting, and multi-vehicle simulations into a unified framework. Due to the large number of transportation technologies and the current model limitations, the workflow could not cover all potential technologies or implications for future/smart mobility. Therefore, this project seeks to enhance many of the existing workflow elements and improve the overall workflow run process while expanding the modeling capabilities of the underlying simulator. The work of this project will focus on the following primary areas:

1. Enhance and automate the ANL-led SMART workflow to enable the simulation of a very large number of scenarios through increased computational efficiency, deployment to both HPC and cloud computing, and addition of extended pre- and post-processing capabilities.

2. Improving traffic flow, transportation management, and connectivity simulation in POLARIS

3. Implementing models of existing (e.g., corner-to-corner ride sharing) modes, new ones (e.g., micro-mobility) and their interactions throughout the existing transportation system in POLARIS (e.g., ride-hailing/transit)

4. Expanding models of traveler behavior and induced demand under new mobility technologies

5. Implementation of freight modeling with new technologies and a realistic simulation model of business firms that participate in goods movement.

6. Updating electric vehicle (EV) charging models

7. Modeling land-use, infrastructure, and transportation interactions in POLARIS and UrbanSim

8. Apply the enhanced workflow to a set of large-scale simulations to explore the impact of a set of future demand and transportation supply scenarios for a diverse set of regions.

Results

Substantial Improvements Made in Deployment of the SMART Workflow.

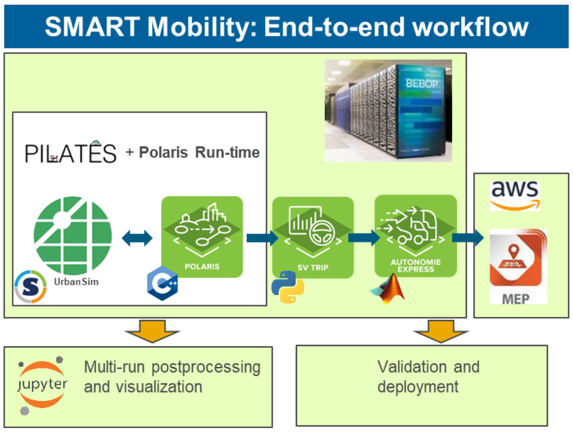

Figure I.1.3.1. POLARIS workflow deployment

This year has seen a significant maturation of the SMART mobility workflows and platforms (Figure I.1.3.1). The EQ/structure query language (SQL)-based distribution platform was simplified and expanded to cover three HPC clusters within ANL to more efficiently deliver large scale studies. The analysis of studies has also been significantly streamlined with key metrics being pre-computed and easily comparable and tooling for in-depth spatial exploration being added to the QGIS GUI toolkit. Our investment in automation continues with our CI/CD infrastructure now covering all aspects of Polaris development including C++ dependencies, web-based publication of documentation and full integration testing of models from raw data (including OpenStreetMap) through model running and into analytics. These automations help to increase the velocity of development while also increasing confidence in the modelling outcomes.

We have also made many improvements to support the wider deployment of Polaris outside of Argonne; the software licensing engine used by Autonomie has been integrated, documentation and getting started guides for users have been expanded and automated to be constantly updated and simplifications to our core codebase have been made to reduce the barrier to entry for new contributors. Our post-run analysis visualizations have been improved and a key milestone in the development of a three-dimensional (3D) real-time visualization of vehicle trajectories was also achieved. Our ability to offer Polaris as a cloud service also hit a significant milestone with the availability of a secure Azure environment for developing easy-to-share deployments. Finally, Polaris documentation has also found a new consolidated home at https://polaris.taps.anl.gov, tying together information from development through to model application and analysis in one publicly accessible location.

Evaluated New Ride-Hailing Operational Paradigms and Strategies

The ride-hailing module in POLARIS was improved through more realistic modeling of driver and fleet operations. Drivers who work for transportation network companies (TNCs) are now integrated into the population synthesized for a region, allowing modelers to capture activity chains, flexible plans to drive for TNCs, and missed home location-related empty miles. On the operator front, detailed and simultaneous operation of multiple TNC operators was included, and competition between them in attracting demand was modeled—all while accommodating various vehicle types, seating capacities, and flexible fare strategies to ensure a heterogenous fleet and its operations.

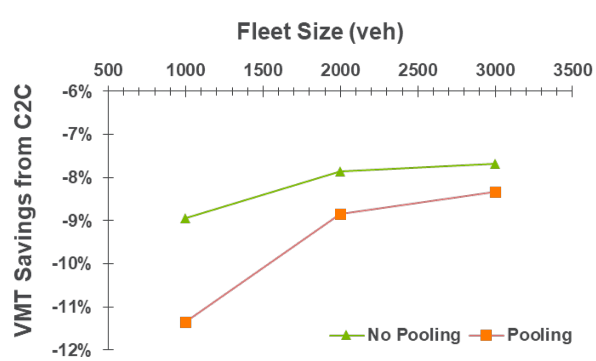

Figure I.1.3.2 Benefit of corner-to-corner routing to minimize fleet VMT

Several studies have been conducted over the past year. One strategy added corner-to-corner routing for TNC vehicles to minimize fleet VMT when serving in dense areas. Results show the ability to lower up to 11% VMT, with additional savings when allowing pooling of all feasible requests in the region (Figure I.1.3.2).

Another study, that implemented an established matching strategy that uses column generation in solving a matching optimization for pooling, explored the ability of shared mobility to replace underutilized transit routes. A case study in Austin, Texas showed a reduction of 59% in average passenger travel time (that includes waiting) when switching from fixed transit to an on-demand shuttle. The multiple operator model improvement was also put to the test through a case study exploring how operator competition impacts TNC revenue, traveler wait times, and the added congestion on the network when one TNC operator is preferred over the other. Various segments of service classes included in this study also reveal how value-of-travel-time is important in identifying users. Finally, a framework for equity considerations of TNC use was formulated and applied to a subset of simulations conducted for last-year's multi-scenario study. While the framework showcases the equity benefits and concerns of TNC use or first-mile/last-mile subsidies, it is also important to use these metrics as objectives to improve equity in a region.

Identified Strategies for Improving Transit

Transit has traditionally been the backbone of mobility solutions in cities, supported by its economies of density. However, it has been losing riders, particularly in North America. Long-term structural trends, such as changing land use patterns and competition from on-demand private mobility platforms, and more recent trends associated with the COVID-19 pandemic, including reduced service and increased prevalence of spatially and temporally flexible hybrid/remote work arrangements, have significantly reduced transit ridership. In a study done in the Chicago Metropolitan Region, transit network is redesigned at different intervention levels. In Scenario 1, existing rail infrastructure (urban and commuter) is preserved while modifying the rail routes (stop sequences), and the bus network is redesigned entirely. In Scenario 2, new rail tracks are constructed in addition to the existing rail infrastructure. The bus network is redesigned entirely, and on-demand transit is introduced as first-mile/last-mile service. Figure I.1.3.3 presents the Lorenz curves and Gini Indices for 45-minute and 60-minute accessible opportunities. In the 45-minute case, the Gini index was reduced from 0.51 in Scenario 1 to 0.20 in Scenario 2, indicating a drastic improvement in spatial equity. Similarly, in the 60-minute case, it decreased from 0.27 to 0.12.

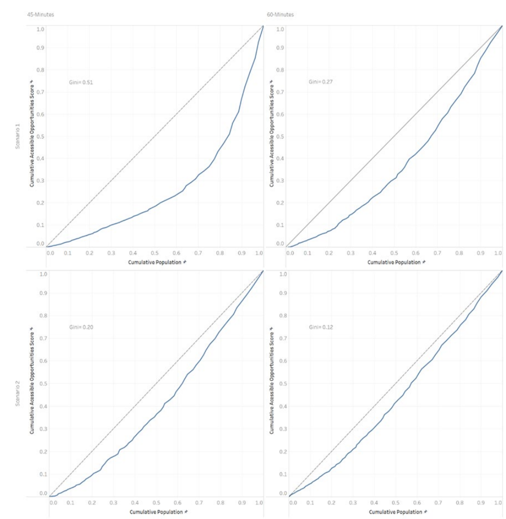

Figure I.1.3.3. Lorenz curves and Gini indices for 45-minute (left) and 60-minute (right) accessible opportunities score for Scenarios 1 (top) and 2 (bottom)

While public transportation is very environmentally friendly on a per passenger-miles basis, the use of conventional diesel vehicles (DVs) contributes to air pollution and carbon emissions, influencing air quality and public health. Electrification of transit buses has emerged as a solution to address these environmental challenges. By transitioning to EVs, cities can significantly reduce harmful emissions and improve air quality. However, EVs still have a shorter range and longer downtime compared to DVs resulting in increased fleet sizes. In studies performed for three different transit agencies (CTA, Chicago; PACE, Chicago; CapMetro, Austin), various deployment targets and EV ranges, it is found that almost 100% bus electrification is possible with 54% to 59% fleet size growth (~1.6 EVs per each replaced DV), as shown in Figure I.1.3.4.

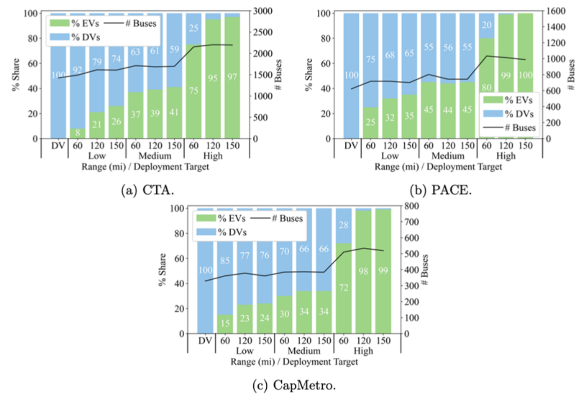

Figure I.1.3.4. Percent share of bus types and number of total buses

Explored Opportunities for Improving EV Charging Performance through Optimization

Previous studies have focused on EVSE deployment under different personal EV stock shares and their impact on waiting time, charger utilization, energy charged, charging time, and greenhouse gas emissions. In this year, spatiotemporal price variance and sensitivity of travelers to changing prices was analyzed. Figure I.1.3.5 presents the average waiting times and average energy charged under different scenarios. In the baseline case, that is the existing EVSE stations with additional plugs to match the number of increased EVs, two sub-scenarios are studied: fixed prices and spatiotemporally varying prices. In each case, the waiting times are very high, demonstrating the non-optimal location of stations despite the high number of plugs. In the next set, EVSE infrastructure is optimized for a given EV stock share (low, medium, high) and travel demand patterns assuming fixed prices. However, the actual prices are fixed or spatiotemporally varying depending on the sub-scenario. If the optimization and reality match, the waiting times are low. If the prices vary spatiotemporally in reality, the waiting times become very high. Moreover, the energy charged reduces significantly due to constrained schedules of travelers. If the EVSE is optimized considering the spatiotemporal variability of prices, the waiting times reduce, and the energy charged moves back up.

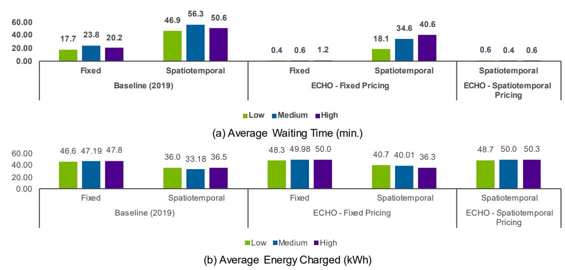

Figure I.1.3.5. Percent share of bus types and number of total buses

Preliminary Results for Vehicle-to-Grid Technology Using ALEAF-POLARIS Linkage

TNC fleet electrification models were improved over the past year. The main highlight is the study analyzing simulations that utilize the vehicle-to-grid power sharing technology and allowing charging decisions to be flexible based on wholesale prices and prices charged at the station depending on local utility provider. One result is showcased in Figure I.1.3.6 that shows the difference in energy consumption when applying different pricing policies (flat rate, wholesale rate, or time of use [TOU] rate). When modeling a fleet of shared automated electric vehicles (SAEVs), demand aspects such as willingness to pool are also considered and figure captures the differential energy consumption across these scenarios of supply and demand.

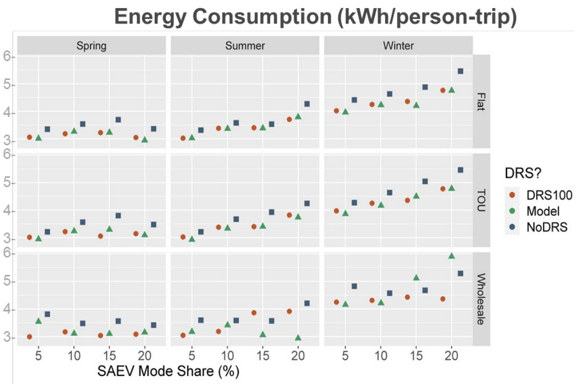

Figure I.1.3.6 Managing fleet energy across 1) flat, 2) time of use, and 3) wholesale pricing

Substantial Enhancements to the Modeling of Core Traveler Behaviors to Support New Studies

In FY 2023, particular focus was given on enhancing the current POLARIS capabilities by developing new models to better quantify the use of micromobility (e.g., e-scooters, Divvy bikes), changes in value of travel time, long-term mobility adoption, ride hailing driver behavior, as well as inter-city traveler behavior. We developed micromobility mode choice models that estimated individuals' behavior towards the choices of docked e-bike, dockless e-bike, e-scooters, and e-scooters as transit access; also, quantify e-scooter safety perception, and e-scooter usage quality-value-satisfaction-loyalty. We also estimated and implemented an e-scooter adoption model to better understand the role of shared e-scooters in urban mobility. Furthermore, a vehicle ownership model was implemented in POLARIS that determines the effects of emerging mobility alternatives (e.g., autonomous vehicles, conventional ride hailing, and autonomous ride hailing), along with the traditional modal alternatives, on vehicle ownership decisions in the households. In addition, we focused on quantifying ride hailing driver behavior using POLARIS workflow to understand drivers' trip acceptance and working time choice behavior. Finally, we estimated and implemented a long-distance travel behavior model that generates travelers' long-distance trip patterns based on trip frequency, destination choice, mode choice, and start time choices for long-distance trips. These developed models enabled us to test various short-, medium- and long-term scenarios of future transportation system operations.

As an example, the improved household vehicle holdings and transactions model was applied to help to investigate how the presence and attributes of various transportation modes, including AVs, influence the relationship between vehicle ownership choices and daily travel. We developed an integrated choice and latent variable (ICLV) model that estimates the choice of emerging modes and their impacts on vehicle ownership based on sociodemographic, trip and attitudinal characteristics. We implemented the model in POLARIS to explore vehicle ownership in relation to emerging mobility alternative choices. A scenario was studied in Bloomington imposing constraints, such as, the parking costs of AVs and conventional cars were increased by 100% while travel times and costs of transit, conventional and autonomous ride-hailing were decreased by 50%. Results suggested an increase in the market share of car-free lifestyle by up to 26% as shown in Figure I.1.3.7. AV ownership was found to decrease more compared to conventional car ownership. Furthermore,

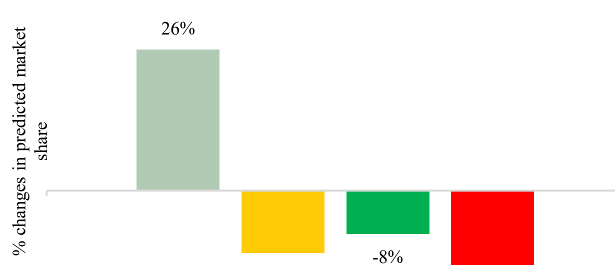

Figure I.1.3.7 Percentage changes in predicted vehicle ownership under future scenarios households with both conventional cars and AVs reduced ownership level the most. This analysis suggests that, at the aggregate level, a coordinated set of policies may lead to considerable shifts in vehicle ownership patterns.

Integrated Freight Module into the Overall POLARIS Framework

The agent-based POLARIS-freight model of freight has been developed and integrated into the POLARIS framework. Detailed models such as firm and establishment generation, supplier choice, freight mode choice, regional fleet operations, and daily truck routing have been fully developed with the POLARIS C++ code base. All models have been refined to match the simulated results with the Freight Analysis Framework dataset in the Chicago and Austin regions. Based on the calibrated POLARIS-freight model, several scenarios have been analyzed, including emerging technologies, such as electrification, micro-hub, delivery lockers, and on-demand deliveries. Figure I.1.3.8 shows the impact of freight truck electrification on the regional grid network. Results indicated that extreme electrification penetration rate has a significant impact on the electric grid, where 70%+ grid nodes will need to provide 50%+ of the current demand by 2040. Since the electricity demand can be reduced by 30% using high powertrain technology, more efficient operation planning for daily freight deliveries is needed to reduce the overload on grid networks. Fleet operation and routing models in POLARIS-freight have been improved to support the decision-making related to mixed-fleet operations, including EV penetration rate, routing for conventional and electric trucks, and route scheduling for truck recharging. Other studies to evaluate traffic impacts of freight activity scenarios, such as higher e-commerce demand and more off-hour deliveries, have also been studied. These operations could help reduce traffic congestion by decreasing passenger and freight activities during the daytime.

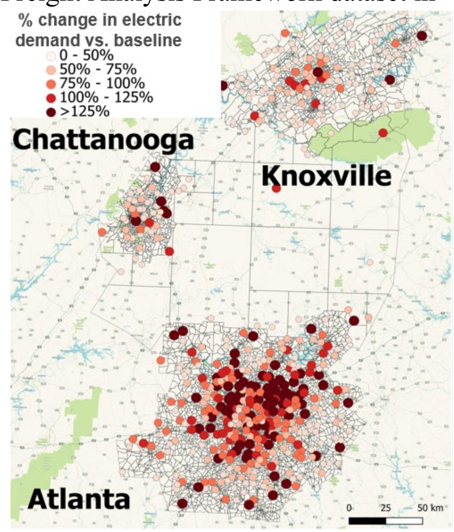

Figure I.1.3.8 Impact of 100% electrification on the grid in 2040

Large-Scale Analysis to Explore the Decarbonization Pathways in Chicago

The research done to explore various system optimization and control strategies, multi-modal travel options, traveler behavior responses and freight modeling was synthesized into a large-scale, focused study to identify potential decarbonization pathways in the Chicago metropolitan region. We sought to explore the joint impact of the various transportation interventions, policies, and technologies under a variety of future demand scenarios, with scenarios determined in close coordination with regional stakeholders including the Chicago Metropolitan Planning Organization, local transit agencies, and the transportation department. The demand scenarios selected included low, moderate, and high EV adoption (15%, 35% and 75% of passenger vehicles and 10%, 25% and 50% of medium and heavy vehicles) and low and high e-commerce and on-demand delivery rates (2% vs 6% year-over-year growth). The supply levers included additional ***transit investment*** (0% vs. 40% increase in frequency for Metra and Pace, 30% increase in speed/frequency on select CTA routes and multiple BRT additions on both), combined ***TNC operational policies*** (first-mile/last-mile ride subsidies at 100% fair reduction to suburban stations combined with restriction to corner-to-corner operations in the city of Chicago), connected ***adaptive traffic signal*** controls (10% vs. 50% connected), and ***congestion pricing*** ($0 vs. time-varying tolls on all expressways) and ***freight off-hours delivery*** policies (5% acceptance vs 15% acceptance with no municipal restrictions on EV off-hours deliveries). This gave a total of six demand scenarios, which were then explored across a factorial study design over five supply levers with each having low and high settings, for a combination of 192 different demand and supply scenarios to explore. This experimental design was then applied to the Chicago Metropolitan Agency for Planning 2040 land use and transportation network forecast—with any adaptations to the network as described above. Each scenario was run for at least 16 iterations, with the first eight allowing the workplace/school choices to change—which allows the forecast to account for responses to changing network level of service in each scenario for those choices. In effect, this enables the models to evaluate rebound effects—e.g., adaptive signals improve arterial travel times which allows travelers to live further from work, which worsens travel times. In fact, this rebound effect was observed for all scenario levers in isolation to varying degrees.

The 192 scenarios run were simulated using the POLARIS modeling workflow on multiple ANL cluster computers using our new Python-EQSQL job manager - POLARISLIB. The impacts of each scenario on key metrics, including VMT, speed, hours traveled, energy use and travel efficiency were then evaluated and compared across regions. Results for the change in overall travel efficiency are shown in Figure I.1.3.9
The results of the study demonstrate the impact that each supply intervention has both in isolation and in combination with each other, for each demand scenario. In general, it was found that optimal combination of interventions depends strongly on the target metric. For example, the study showed that the best combination for improving network speed was signals, pricing, on-demand delivery, and high electrification, which resulted in an overall increase of 4% increase in speed. However, this combination would result in an increase in overall travel efficiency of 51.7% instead of the optimal increase of 61%. If, however, we add the signals lever to the optimal combination for overall travel efficiency, this would give an increase in travel speed of 2.2% at the same gain of 61% in efficiency. So, while this is suboptimal from a speed perspective it gives a better overall balance of outcomes. Therefore, it is critical to evaluate such interactions for a wide variety of metrics and have broad feedback and input into how metrics should be weighted, in determining optimal pathways to increase efficiency.

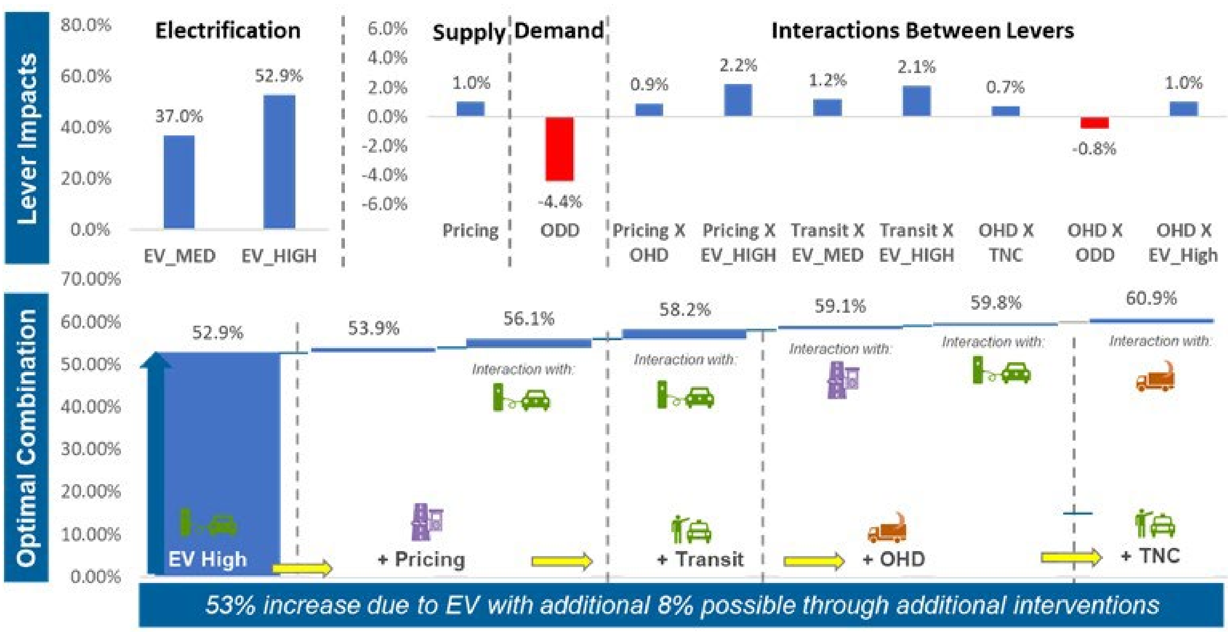

Figure I.1.3.9. Change in travel efficiency (productive miles per kWh) for each lever along with the optimal combination leading to a 61% improvement in efficiency

Conclusions

Over the previous year, substantial accomplishments have been made in expanding the features and capabilities of the SMART Mobility workflow and improving the process of deploying the toolset and running simulations using the workflow. The representation of multi-modal travel and new mode options in the simulator has expanded including new fleet management and optimization algorithms for corner-to-corner operations, shared ride optimization, and competitive operational strategies for multiple fleets. We also expanded micromobility and first-mile/last-mile options and developed new methods for optimizing shared mobility modes. Demand in POLARIS has continued to include joint-travel decisions, long-term vehicle holdings and an expanded understanding of the interaction between time-use and value of travel time. The representation of freight in POLARIS, through the updating of the agent-based freight modeling framework to include integration with land use and forecasting of firm synthesis and asset choices has also been improved and is now calibrated and demonstrated for Austin. The capability of modeling electrification of new and existing modes, such as TNC, transit, and freight vehicles has also been expanded with EV charging behaviors, EVSE siting optimization, and new fleet charging strategies and demonstrated for both transit and local delivery fleet electrification. The new capabilities were demonstrated in a series of individual simulation analyses as well as in a large-scale study for the Chicago region.

Key Publications

1. Bostanara, M., T. H. Rashidi, N. A. Khan, J. Auld, M. Ghasri, and C. Grazian. The Co-Determination of Home and Workplace Relocation Durations Using Survival Copula Analysis. Computers, Environment and Urban Systems, Vol. 99, 2023, p. 101898.

2. Cokyasar, T., A. Davatgari, and A. K. Mohammadian. An Optimization Model for Solving the Route Clustering Problem. In The 14th international conference on ambient systems, networks and technologies (ANT), No. 220, 2023, pp. 180–186.

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I.1.4 Characterizing Behaviors and Capabilities for Emerging Connected and Automated Vehicle Technologies and Sensors (Argonne National Laboratory, National Renewable Energy Laboratory)

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Project Introduction

While DOE researchers and many others have conducted numerous studies to develop and assess the energy and mobility implications of a wide range of CAV technologies, these studies are only as robust as the data used to inform the study's assumptions and models. Specific to the efforts discussed in this proposal, several critical data gaps regarding the characteristics of emerging CAVs, their sensing/communications capabilities, and their subsequent utilization and performance have been identified and proposed for expanded experimental investigation and characterization. Addressing key data-gaps identified during DOE's SMART Mobility Consortium efforts, this project seeks to collect, analyze, and distribute high-fidelity operational, utilization, and efficacy data under real-world usage conditions for a range of emerging, but commercially available, CAV technologies.

Objectives

The project is structured into four separate, yet interconnected tasks designed to ensure that a comprehensive collection of state-of-the-art CAV data is being collected. The overarching objective of Task 1 (Light-Duty [LD] CAV Functionality in Real-World Operational Scenarios) is to provide a bountiful data resource for modelers and researchers to validate assumptions, simulations, and insights of CAV performance, efficacy, and impacts on efficiency. Capturing extensive operational data and comprehensive measurements will provide insights into many questions that are still paramount to assessing the impact of disruptive CAV technology.

The objective of Task 2 (Medium/Heavy Duty [MD/HD] Connected and Automated Vehicle Data Collection) is to provide a bountiful data resource for modelers and researchers to validate assumptions, simulations, and insights of MD/HD CAV performance, efficacy and impacts on efficiency. Capturing extensive operational data and comprehensive measurements will provide insights into many questions that are still paramount to assessing the impact of disruptive CAV technology. Some of these questions are similar to the light-duty vehicle (LDV) questions above, but some are unique to the performance characteristics of these slower and heavier vehicles as well as some unique use cases such as long-haul trucking.

The main objective of Task 3 (CAV Sensor Performance) is to provide detailed CAV sensor performance under a variety of environmental and real-world usage conditions. This includes range, resolution, robustness, and power-draw of CAV sensors under realistic conditions, including varying environmental and weather conditions, as well as the range, latency, reliability, and bandwidth of various vehicle and infrastructure connectivity technologies. The detailed operational characteristics (i.e., range) for a range of CAV sensing technologies under real-world usage and environmental conditions will be made available by ANL for other DOE modeling and research efforts.

The overarching objective of Task 4 (Experimental Testing and Evaluation Methodology Investigation) includes representing DOE's interest in test procedures that provide realistic, real-world impacts of technology, including SAE discussions on a fuel economy test procedure that addresses currently available ADAS features. As the SAE effort progresses, attention will expand to more advanced ADAS features in the future. Deliverables will include recommendations for experimental researchers to design proper tests that fairly quantify CAV features.

Approach

Figure I.1.4.1 outlines the project's approach to reach its objectives. Based on input from customers, signal lists and data acquisition characteristics were defined that guide the experimental data collection and analysis performed on LD and MD/HD vehicles as well as sensors and connectivity setups.

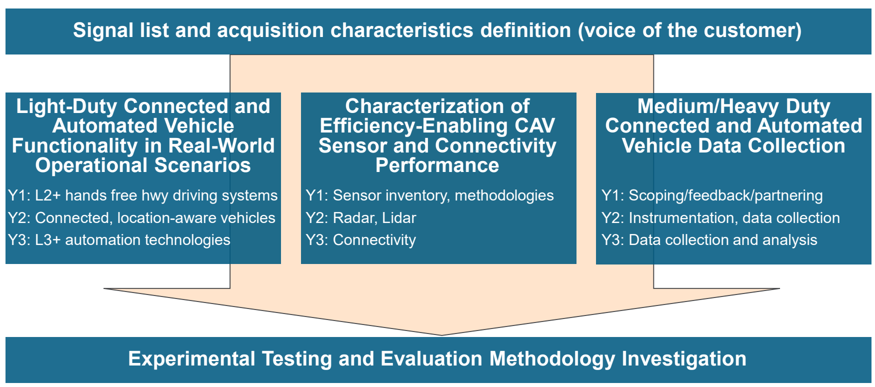

Figure I.1.4.1 Visualization of the *Characterizing Behaviors and Capabilities for Emerging Connected and Automated Vehicle Technologies, Sensors, and Connectivity* project approach

The LD data collection leverages a mobile data collection platform developed as part of the Oak Ridge National Laboratory (ORNL)-led Real-Sim SMART 2.0 project and focuses on SAE Level 2 automation with hands-free highway driving in Year 1, connected or location-aware vehicles in Year 2 and Level 3+ automation technologies in Year 3. The sensor and connectivity performance task is set up to develop evaluation methodologies in Year 1 which are applied to evaluate radar and Light Detection and Ranging (LiDAR) sensors in year 2 and connectivity technologies in Year 3. The MD/HD data collection leverages on-road CAV deployments with Year 1 focusing on scoping and partnering with Years 2 and 3 targeting instrumentation, data collection and analysis.

The information, data, and findings from the three experimental tasks will be shared with the larger community leveraging the Livewire platform and learnings will directly feed into the recommendations regarding experimental testing and evaluation methodologies (Task 4).

Results

Task 1: Light-Duty (LD) CAV Functionality in Real-World Operational Scenarios

Year 3 Testing Full Self Driving function in Tesla Model 3

The task for year 3 was to investigate the performance of Tesla's Full Self-Driving (FSD) automated driving system in the context of energy consumption in various real-world, on-road driving scenarios. The deliverable is an on-road driving dataset that can be used by any researcher interested in analyzing or comparing their research to the realistic, real-world performance of production CAVs. Tesla's FSD is an optional feature that was slowly rolled out to beta testers in 2022. Tesla deployed a few upgrades and a revision recall over the duration of our program. FY 2023 testing on the 2020 Tesla Model 3 test vehicle began in early April. To avoid changing variables early in the program, upgrades were not installed until a sizable set of tests were performed. After 70 tests were completed from April until July on FSD v10.69.3.3, in July 2023, the FSD version was upgraded to v11.3.6 (the most recent at the time) and 13 more tests were run with the newer FSD version.

Test Hardware and Software

The goal of the project is to collect extensive data on the vehicle and how it reacts and interacts with the driving environment. Like year 1, a perception kit with data acquisition was used to collect vehicle operational data, LiDAR, radar, and camera data (using neural network object classifier technology). ANL employed its "APAK-v" perception and data acquisition system which for Year 3 was upgraded with better cameras in waterproof enclosures, and a hot-swappable battery power supply to facilitate continued data collection throughout a test day. A new GUI and driver test procedures were developed and refined for ease of use and to prevent loss of data. Also, we added pedestrian data classification and location (camera fusion with LiDAR data) so that the test data can be collected in routes with high pedestrian cross traffic. The data also includes an extensive list of signals from the vehicle communications network revealing powertrain operation and driving automation system signals and parameters. The vehicle's own GPS signal was found to be quite robust in driving real-world routes (glitches due to satellite obstructions were rare). The new perception system and data collection computer are shown in Figure I.1.4.2.

Figure I.1.4.2 At left: Perception system including LiDAR and 6-camera array, at center: system mounted on test vehicle, at right: purpose-built perception computer with neural network object detection and sensor fusion in real-time

Test Routes

In Year 1 of the project, the Tesla Autopilot was tested on highway routes and some of the suburban artery routes, but given the additional capabilities of FSD, additional driving routes were explored in Year 3 (FY 2023). Driving in areas with frequent stop signs and traffic lights is an area of interest in this year's testing. A significant effort went into designing the routes for the best results. For congested, urban driving, one would expect tall buildings in the area that interfere with GPS reception. For this reason, a special urban loop was laid out in the vicinity of Midway Airport in Chicago. As there are no tall buildings near the airport thus reducing the problems encountered with GPS signals. Route development also considered avoiding confusing intersections that may require frequent driver interventions. The goal is to find routes that test the vehicle's speed choices and accel/decel characteristics when responding to its lead vehicle, other traffic, turns, stop signs, and traffic lights in FSD. Turns were typically right-hand turns to reduce crossing lanes of traffic. Also, of interest was to repeat a given route many times to find randomness in the vehicle and the environment.

The test routes that were developed include:

- Highway – a stretch of I-55 going south from Argonne that has 55 and 65 mph speed zones.
- Pedestrian Loop – a short loop that encounters two zones with a high density of pedestrians.
- Suburban – suburban artery road and shopping district road (mix of 35, 45, and 55 mph speed zones)
- Urban (near Midway Airport) – urban loop of frequent stop signs and traffic lights

Table I.1.4.1 contains various properties and calculations from the main routes tested in FY 2023 testing.

Table I.1.4.1 Tesla FSD Dataset Consists of Four Main Routes

	Number of Tests	Average Elapsed Time (s)	Average Distance (mi)	Average Speed (mph)	Percent Zero Speed	Average Energy Usage (Wh/mile)
Highway	18	2415.0	32.2	48.3	4.9	247.9
Pedestrian Loop	21	1342.5	6.5	17.7	25.4	244.3
Suburban	21	3901.2	29.3	27.1	16.9	238.3
Urban	17	1183.8	4.1	12.7	18.8	360.7

Data Collection

A total of 83 tests were conducted. A few of the tests were run with a companion vehicle driving specified speed maneuvers to exercise the test vehicle and better analyze the car-following behavior. The total test distance logged was 1,545 miles, covering 52.6 hours of testing. Some of the driving settings were varied to better understand these driver-selectable settings. Also varied were other driving choices like which lane, and time of day (lighting conditions). Rainy days were not driven because in some cases the FSD system cannot be activated when visibility is lowered by rain.

Post-processing

The raw test data required considerable post-processing to yield a clean, flat 10 Hz data file that can easily be used by other researchers. Each route was separated into phases to allow easy analysis. For example, the highway route data was logged for the whole trip, but the actual highway driving segments were tagged separately in the data so that batch processing can exclude off-ramp segments without additional processing. The video camera objects were classified using an artificial neural network (YOLOv3) and fused to the LiDAR data during testing using the perception kit. In post-processing, vehicle objects were also classified by the lane they were in relative to the ego vehicle. This high-level data presentation brings the data into easily readable text files each with 277 signals of information at each timestamp.

Insights

The capabilities of FSD have significantly improved compared to Year 1 Autopilot mode. Furthermore, the FSD upgrade to v11.3.6 in July appears to be more situationally aware and can better anticipate the actions of surrounding vehicles. The vehicle takes steps earlier to avoid abrupt or unnecessary braking events. For example, in Year 1, Autopilot often waited too long to change speeds to allow room for a merging vehicle coming from a merge lane. The latest FSD can make small speed adjustments earlier to avoid excessive slowdowns before the merge.

The primary concern of automated driving in the context of energy impact is unnecessary or excessive braking events requiring subsequent acceleration back to speed. There were instances captured where braking persisted beyond the time that a situationally aware human would end braking and transition to acceleration because the vehicle in front had clearly exited the lane by turning onto another street. Data analysis reveals energy loss during these excessive braking events; however, since these incidents are brief and infrequent, their overall impact on trip efficiency is likely minimal. One promising assumption can be made that as the industry advances the technology to avoid these 'glitches' to enhance the driver experience the results may align with DOE goals of saving energy through driving automation. On the other hand, this may not be true of all automated driving features. Certain automated behaviors, like elective lane switching, may not correlate energy savings with improved driver experience. Issues such as these are deserving of further study and monitoring with each new generation of production CAV technology.

Posting to LIVEWIRE
The data files were organized and uploaded to DOE's Livewire Data Platform for open access by any interested researcher. Livewire has been an important tool to share large data sets with other researchers. It also allows us to track the interest in the data to help optimize future test programs for more widespread use. As evident in the Year 1 data from this program (Tesla Autopilot testing), Livewire counted 3,375 file requests with 62 GB of downloaded data. This program is another example of how advanced vehicle testing programs investigating existing production technology can successfully leverage its impact many times over by researchers all around the world who are aiming to make revolutionary breakthroughs in personal mobility automation.

Task 2 Medium/Heavy Duty (MD/HD) Connected and Automated Vehicle Data Collection

The National Renewable Energy Laboratory (NREL) worked on significantly improving its video analysis code using MATLAB Computer Vision Toolbox to Python with YOLOv5 to now include a two-tiered intrusion identification system for the columnized data shared on Livewire (see Figure I.1.4.3). First a warning "yellow alert" of a possible lane intrusion beginning when approximately 20% of the object crosses the identified lane followed by an active intrusion alert "red alert" of a definite lane intrusion when 50% of the object crossed the identified lane. In all, 72 truck test days were shared with a mix of two and three truck platooning on a 329-mile test route in southern Indiana with varying road grade, construction zones and multiple freeway interchanges. Eight days include video processing with object detection using YOLOv5 converting the object information into columnized data output.

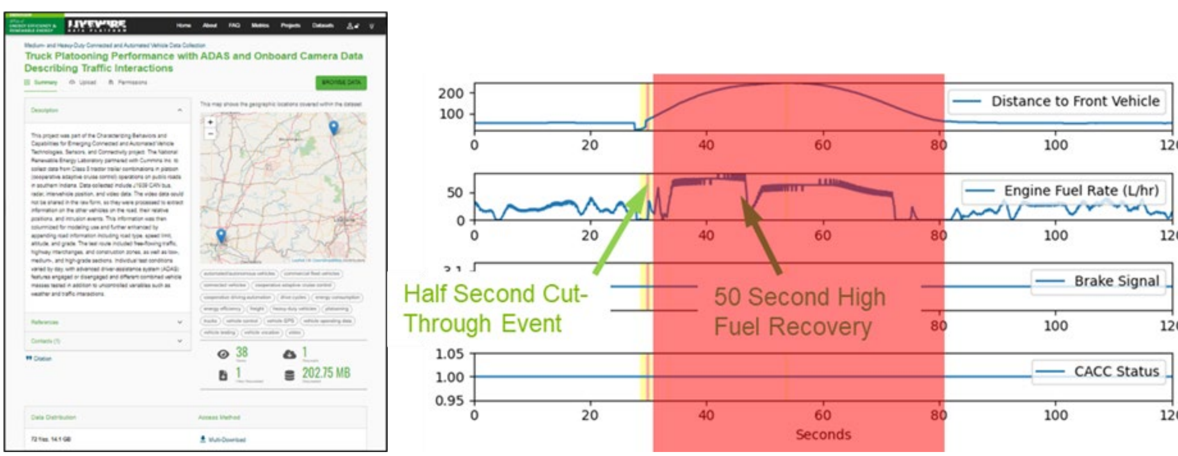

Figure I.1.4.3 Livewire project data sharing page and example cut in event

NREL has completed initial fuel consumption analysis of four vehicle intrusion events identified with the above object intrusion identification code. Fuel use can stay the same or increase by 70+% for the following vehicle when compared to the same section of road on a different day without an intrusion. While each event is quite unique in context and duration; one common finding is that the cut in "event" duration is a fraction of the recovery duration which can amplify the fuel consumption impact as the trailing vehicle works to regain its position. In the example shown in Figure I.1.4.3, a half second cut through to an exit event resulted in almost a minute of very high fuel rate to catch up resulting in a 73% increase in fuel consumption over that section of highway. NREL continued analysis of data posted to Livewire including fuel consumption impacts of intrusions and classification of “yellow” stage possible intrusion events (see Figure I.1.4.4). Most of the possible intrusion events were in fact processing errors, but one was a real event not previously identified. Thirty-eight events were due to lane line identification errors—such as the absence of a lane line during a merge where the software widened the lane and included a vehicle that was going to merge behind the truck or when the lane lines disappeared while going under an overpass on a sunny day. An additional 21 events were due to GPS misclassifications that improperly put the truck on the divided freeway when it was currently adjacent to it but not on it. Additional events were a result of vehicles in the adjacent lane passing when their ID box was too large, or they swayed too close to the lane line. Towards the end of the year Cummins agreed to transfer an additional 20+ test days of video for analysis and processing and sharing that on Livewire is a focus of Q124.

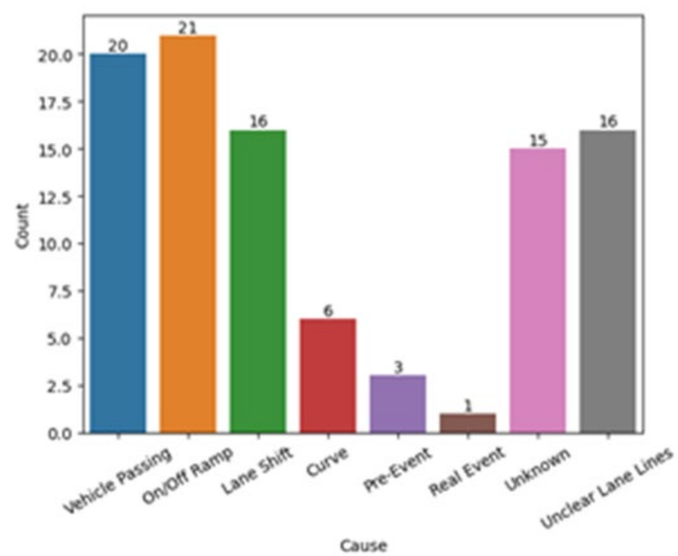

Figure I.1.4.4 Causes of potential intrusion event alerts

Partnership outreach continued throughout the year. Partnership agreements were nearly solidified with both Locomation and Plus AI but then both were cancelled due to business headwinds with those partners. However, discussions with DriveOhio moved forward substantially and a memorandum of understanding (MOU) was initialized at the end of the fiscal year. Completing the MOU, securing data collection and analysis of the DriveOhio rural truck platooning project will be a focus of the final two quarters planned for this task.

Task 3 CAV Sensor Performance

Improved Data Collection to Include Quantitative Weather Metrics

The primary adjustment made in the FY 2023 sensor characterization effort was to log a dataset that contained quantitative weather data synchronized with the real-time sensors array. These improvements were achieved by partnering with Argonne’s Testbed for Multi-Observational Studies (ATMOS) which was able to open up data sources such as the Vaisala FD-70 present weather sensor and the ANL 60-m Meteorological tower that contains critical data about the environment and weather conditions, enabling us to extract

Figure I.1.4.5 Data collection sensor array and stop sign positioning.

deeper insights into the environmental conditions' impact on CAV sensors. In addition to the weather data improvements, we also acquired a state-of-the-art LiDAR used for our primary analysis, an Ouster OS2-128. We also logged with a Velodyne VLP-16, VLP-32, and Mako red, green and blue (RGB) camera. These sensors were installed onto a static array, positioned toward two static stop signs. Figure I.1.4.5 shows an overview of the sensor array and targets used for data collection. This setup was ideal to log for long durations, without powering off the sensors. Data was logged from March 1st to April 16th, with instances in between where logging was halted due to maintenance/debugging.

Collected Dataset

Overall, there was over 5 TB of data logged from the sensor array. There was significant effort put toward resampling, organizing, and distilling this dataset into a usable format for external researchers. By resampling all data to a set number of frames per log, the overall size of the dataset was reduced to ~200 GB. The file types were chosen since they are open-source and simple to use for users, with a wide variety of options for tools. Figure I.1.4.6 shows the flow diagram for each sensor saved as the designated file type. The dataset has been organized and uploaded to https://livewire.energy.gov/ds/ld-cav-functionality/raw-lidar-camera.

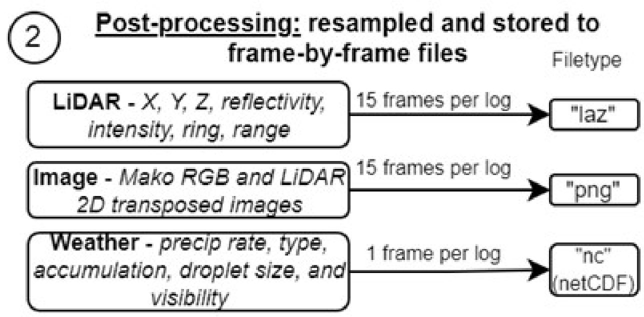

Figure I.1.4.6 Post-processing diagram for saving sensor metrics to dataset files.

LiDAR Characterization Results

The primary analysis done with this dataset focused on the Ouster OS2-128 LiDAR by investigating the LiDAR metrics and how they were impacted from the returns on one of the stop signs. From the raw LiDAR point cloud, we calculated the total mean number of points received from the stop sign (ss_pnts), the mean and variance intensity of all points (ss_intm, ss_intv), and the mean position of all points (ss_xm, ss_ym, ss_zm). We used data from the Vaisala FD-70 (precip_intensity, reflectivity, mean_diam) and from the 60-m meteorological tower data at Argonne (https://www.atmos.anl.gov/ANLMET/). This data source provided us with net solar radiation, relative humidity, average temperature, and an additional precipitation reading, all at 1-hour increments. Figure I.1.4.7 shows a snip of time-series plots with an aligned X-axis to overlay the correlations with some signals. Some unexpected findings from this analysis are:

- Net solar radiation (W/m^2) has most of the impact on LiDAR intensity, meaning, sunlight intensity can cause fluctuations in the intensity values of LiDAR point clouds, causing mishaps with object classification models that may rely on LiDAR.
- Precipitation intensity and mean droplet diameters have little impact on the LiDAR intensity, but they do impact the total number of points returned and the ranging accuracy (i.e., positioning in the X-axis).

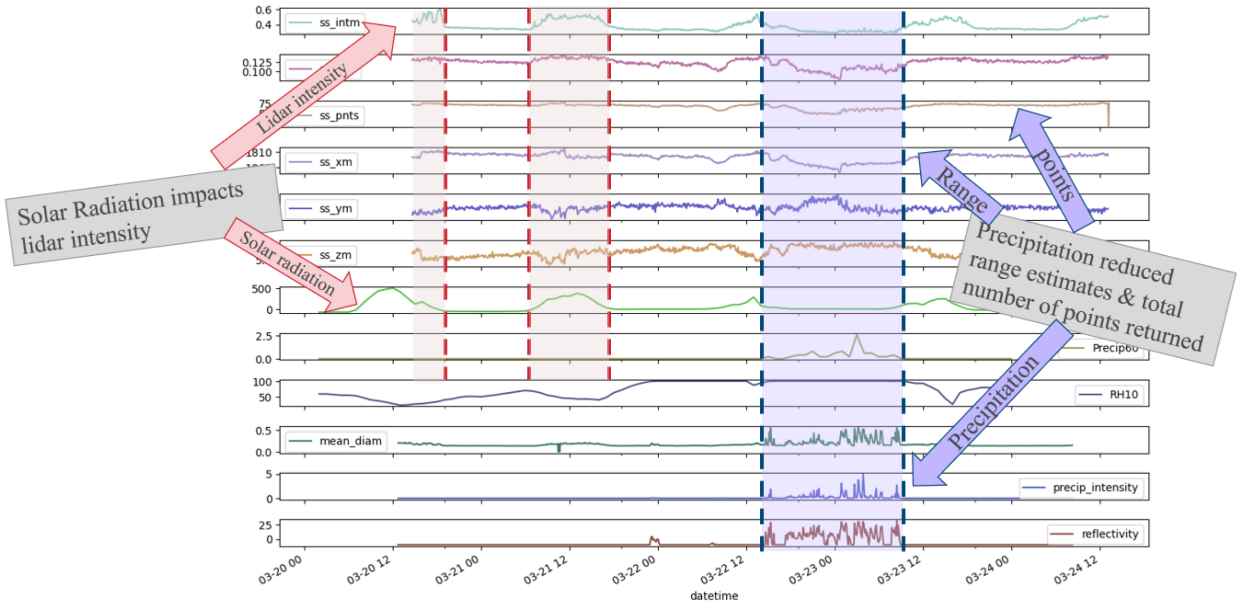

Figure I.1.4.7 Time-series plot from 3/20/23 to 3/24/23 showing LiDAR and weather measurements

Task 4 Experimental Testing and Evaluation Methodology Investigation

Leading SAE Standards Task Force on Testing Automated Vehicles for Emissions and Energy

Background

The SAE Light-Duty Vehicle Performance and Economy Measure Committee is responsible for a number of key SAE dynamometer vehicle testing standards related to emissions and energy consumption for conventional, hybrid, and electric vehicles. The procedures to determine the dynamometer road load based on track testing are also within this committee. In 2019, the committee decided that a task force should be formed to consider how CAVs would be tested for emissions and energy use. The objective of this small SMART task is to support the SAE task force by providing input and guidance leveraging the other SMART activities at ANL and the DOE SMART program at large. In 2023 the task force chair stepped down and the PI of this project became the chair. Since April 2023, monthly meetings have been held and additional members recruited to the task force. The task force currently has 24 members, each representing a diverse array of stakeholders—including light- and heavy-duty OEMs, the U.S. Environmental Protection Agency, E&C Canada, test equipment suppliers, and academia.

Problem Breakdown

Discussions in early meetings led to the identification of specific sub-tasks to structure the activity.

- **Current Testing Paradigm** – run existing procedures with deviations to accommodate CAVs.
  - Find methods to test and correct for the additional auxiliary loads that occur when the automation system is active.
  - Standardize methods to drive a highly automated CAV (Level 4, Level 5) on a dynamometer without standard vehicle controls.
- **Lead-Car Following Method** – based on existing drive cycles, run a simulated lead car, the test vehicle driving with its ACC system.
- **Frameworks for Future CAV Testing** – this method will require a complete reworking of testing protocols in the lab.

- Requires a paradigm shift from drive trace to trip/route.
- "XIL dyno" testing is needed with environmental information provided to the vehicle, either by real-time standard messaging or with vehicle sensor stimulation.

Process to Develop for Future CAV Testing Methods
A development process framework was conceived to address the wide scope of future testing solutions. The process has several sequential tasks where each task feeds into the next, they are:

1. **A comprehensive list of all current and future CAV features** that may affect driving efficiency. A CAV may make lane choices, speed modulation, and many other specific decisions as it responds to the specific driving scenario. A working draft of these features has been developed.
2. **Define driving scenarios for these features** and match these scenarios to the features. Specific CAV features are best tested in scenarios that are specifically suited for that feature. Representative scenarios must be developed based on the actual properties of our road networks. Data from existing and future road and transportation networks will need to be leveraged. This sub-task is in its early stages and will require significant resources and time to develop to maturity.
3. **Define specific testing frameworks**. The specific testing tools, facilities, and capabilities along with the testing process/flow must be defined to obtain proper and robust results of the impact of a specific CAV feature on the vehicle's efficiency (or emissions).

An important consideration for any of the future CAV testing approaches is the need to obtain a baseline human driver benchmark test for any given CAV feature or function. Finding approaches that yield satisfactory comparison baseline results with which to compare CAV results is a significant challenge.

Conclusions

Task 1 (Light-Duty [LD] CAV Functionality in Real-World Operational Scenarios) successfully achieved the goal of instrumenting and testing arguably the most advanced automated driving system in production, The created datasets have value in many aspects of CAV research. The performance and capabilities of production CAV systems include all the real-world compromises, trade-offs, and limitations of current mass-produced hardware and provide a benchmark to guide the development of future cutting-edge prototype technology. The experiments utilized advanced hardware and software for data collection, including perception kits, improved cameras, and data fusion techniques. Various test routes were explored, emphasizing city environments and traffic scenarios. A total of 83 tests covered 1,545 miles over 52.6 hours. Data underwent rigorous post-processing for sharing on DOE's Livewire Data Platform, fostering collaborative research in autonomous mobility. The program's success lies in its ability to leverage data for global research, aiming to revolutionize personal mobility through automation.

Task 2 (Medium/Heavy Duty [MD/HD] Connected and Automated Vehicle Data Collection) successfully achieved the goal of collecting, processing, and sharing CAV data on Livewire. The first partnership's HD Truck Platooning data shared this year has had 474 file requests by other researchers for other analysis beyond this project. Because of the success this project demonstrated the project partner is presently sharing additional data to expand what has been shared on Livewire already. NREL's video processing has continued to improve on event detection as well as fuel consumption impacts of intrusion events being analyzed. Two additional partnerships this year did fail to produce the planned shareable data due to business setbacks for the partners, but a third partnership is moving forward and is expected to produce additional shareable MD/HD CAV data from different partners, systems, and situations.

Task 3 (CAV Sensor and Connectivity Performance) accomplished the goal of further understanding the impact of environmental conditions on energy-efficiency-enabling CAV sensor technologies. We have realized proper methodologies of evaluating production-level perception systems to not only include the sensor, but also include the algorithm responsible for processing the raw sensor data. We have an expanded understanding of how to quantify the external and environmental conditions around a vehicle through partnerships with atmospheric research scientists. We have successfully published an open-source dataset for external researchers to pursue more insights, that is unique to include synchronized weather data. We have found some unique insights ourselves, that may influence additional research to be done to dig into solar radiation or precipitation intensity impacts on LiDARs, to be published in a peer-reviewed conference.

Task 4 (Experimental Testing and Evaluation Methodology Investigation) has kickstarted a now ongoing effort to design and establish standardized methods for integrating CAVs into conventional testing procedures, aiming to assess their influence on energy consumption and emissions. In FY 223, progress notably advanced when the project's PI was appointed as the chair of the task force committee. The team introduced numerous definitions and workflow frameworks, laying a solid foundation for ongoing development. With sustained backing, this initiative holds the potential to transform CAV energy efficiency research. It aims to unite the community under standardized scenarios and testing methods, capitalizing on the significant advancements in vehicle test and measurement technology that are being developed to make CAVs safe and reliable.

Key Publications

1. Goberville, N., Ahmed, S., Iliev, S., and Pervan, B., "Automated Vehicle Perception Sensor Evaluation in Real-World Weather Conditions," SAE Technical Paper 2023-01-0056, 2023, https://doi.org/10.4271/2023-01-0056.

Accepted abstracts

1. "On-road testing to characterize speed-following behavior in production automated vehicles," Michael Duoba, Tinu Vellamattathil Baby, Jorge Pulpeiro Gonzalez, Argonne National Laboratory, SAE 2024 WCX

2. "Elective Lane Change Observations for Tesla Full Self-Driving," Jorge Pulpeiro Gonzalez, Tinu Vellamattathil Baby, Michael Duoba, Argonne National Laboratory, Baisravan HomChaudhuri, Illinois Institute of Technology, SAE 2024 WCX

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I.1.5 Optimizing Drone Deployment for More Effective Movement of Goods (Idaho National Laboratory)

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Project Introduction

Aerial drones offer the potential to improve the delivery of goods in the last mile, especially for time-sensitive, small, and localized deliveries. Drones may enable direct routing, faster deliveries, reduced congestion, and reduced labor. Typical drones are powered by on-board batteries, whose specific power acts as key limiting factor in UAV applications. Hence, there is a need to study and understand the energy consumption for drone deliveries, the different ways that drones could be deployed, and how the different delivery methods impact their use and energy consumption. Additional considerations include the energy impacts of different environmental and operating conditions, and how to optimize drone deliveries for cost and throughput. This project will answer critical questions about how aerial drones can be deployed to deliver goods most efficiently and enable strategic improvements in the mobility system as a whole. This work will provide a deep, practical understanding of the energy and business impacts of drone use.

Objectives

This project will determine the most efficient and effective methods to deploy a fleet of drones for goods delivery by generating insights on:

- Impacts of flight paths on the cost of drone deliveries, in terms of time, speed and energy needs of drone deliveries.
- Strategies for effective drone fleet sizing, dispatching, scheduling, and charging that meet the needs of various users and business use-cases.
- The total energy and time needed to deliver packages by drones compared to ground-only vehicles in several different scenarios.
- The effectiveness of different drone types for goods deliveries in different missions and conditions.
- The effect of environmental conditions (e.g., ambient temperature) on the energy efficiency and mission capability of drones and drone charging.
- The impacts of using a mixed fleet of air and ground vehicles to serve a full set of delivery needs.
- The set of tools that can help inform users and industry about alternatives and improvements in delivery energy.

The project will also provide critical data to researchers developing models for drone operations and an independent evaluation of drone technologies for multiple stakeholders.

Approach

The project will:

- Test several types of drones to examine their impact on operations and performance in different outdoor conditions and perform detailed temperature and component energy testing in a laboratory environment.
- Develop relevant delivery scenarios based on industry input and perform optimization analysis on different drone operations and conditions to demonstrate how to improve drone deployment methods.
- Perform physical experiments based on optimized scenarios to show validation of results and gather key insights using tested drones.
- Develop a public tool that will provide information about drone delivery energy and deployment strategies to industry and interested parties.

See Figure I.1.5.1 for a representation on how these elements interact.

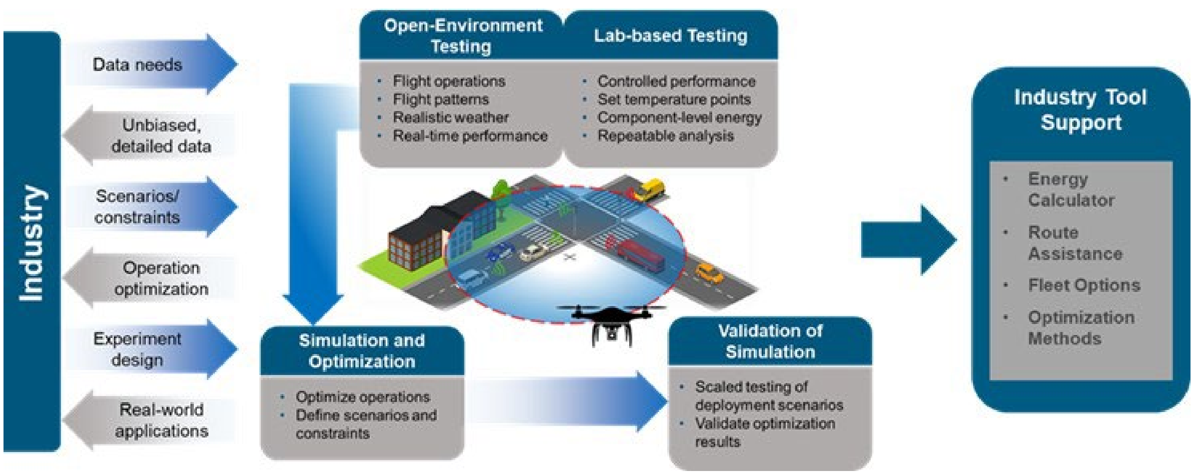

Figure I.1.5.1 Approach to drone optimization.

Results

During FY 2023 the project examined the impacts of a mixed fleet of air and ground vehicles in the process of providing a realistic and full-service delivery service. It looked at the impacts of weather conditions on the availability of each class of drone vehicle and looked at how different vehicles would impact the complete delivery and energy profiles as we implemented a combined fleet of traditional cars and drones. The project considered four types of drones: small rotary (such as Tarot 650), large rotary (such as DJI Matrice 600 Pro), small VTOL (such as Wing’s Hummingbird), and large VTOL (such as Wingcopter 198). More detailed specifications of these categories of drones can be seen in previous versions of the annual performance review for this project.

First, our analysis looked at the operating parameters of different air vehicles based on wind-speed and temperature. Table I.1.5.1 shows the approximate limits of weather-related constraints on use based on manufacturer values for allowable operating conditions. Note that some values for the small rotary and small VTOL are approximations as exact values were not provided for the drones tested. Also note that the VTOL systems are not intended to be operated below freezing due to the risk of icing on the wings.

Table I.1.5.1 Weather Limitations for Each Category of Drone.

Drone types	Low temperature (F)	High temperature (F)	Maximum wind (mph)	Precipitation
Small Rotary	*25	*100	*15	Light rain
Large Rotary	14	104	17.9	Light rain / snow
Small VTOL	*32	*105	*25	No icing / light rain
Large VTOL	32	113	33	No icing / heavy rain

To examine the impact of weather on the availability of using drones to perform deliveries, we examined the weather data from the National Oceanic and Atmospheric Administration (NOAA) found at https://www.weather.gov/. We examined three locations, Idaho Falls, Idaho, Chicago, Illinois, and San Francisco, California. We looked at whether temperatures would prevent flying for part of the day or all day (Total Temp is all days affected by temperature—whether full day or part of the day), whether the wind levels would be higher than the allowable values for longer than five minutes, and whether there were more than

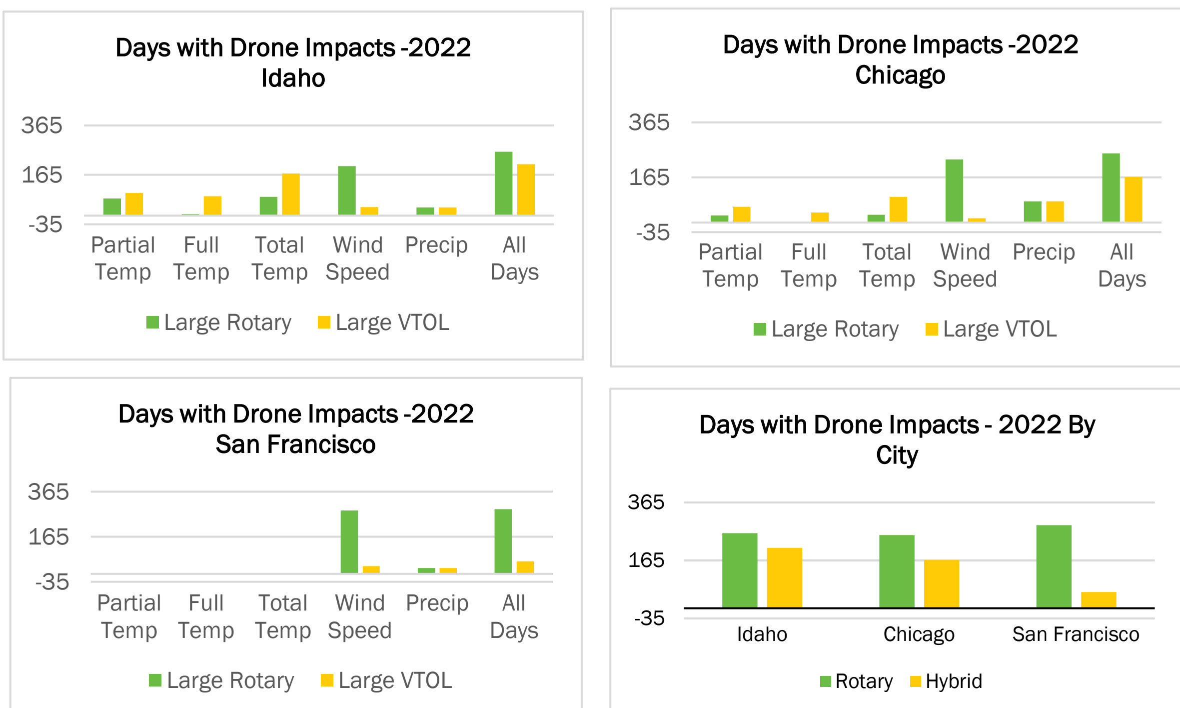

Figure I.1.5.2 Number of days with impacts from weather in different locations

trace amounts of precipitation. The results comparing the impacts for the large rotary drone and the large VTOL for all of these locations is shown in Figure I.1.5-2. In Idaho Falls, the large rotary was impacted 70% of days, and the large VTOL was impacted 57% of days. The Chicago area was impacted by 69% and 45% of the days, and San Francisco was impacted 78% and 16% of the days.

We then examined in more detail the impacts of weather based on actual business hours versus the entire day. For this analysis we again used the weather data from NOAA and considered the weather in San Fransisco, California. (We used delivery data in the San Francisco area for comparison analysis as shown.) Figure I.1.5.3 shows the number of business hours which would limit the use of different types of drones in each month over a year. Business hours were defined as 8:00 AM to 9:00 PM. None of the drones were affected by temperature limitations and were mostly limited by wind speeds. The impact of precipitation was factored for all the drones in the same way. As seen in the figure, there were significant differences in rotary versus hybrid VTOL drones. The rotary drones had lower wind tolerance, so the small rotary drone was restricted in 40% of the business hours, whereas the large rotary drone was affected 30% of business hours. Meanwhile, the small VTOL drone was only affected 7% of the total business hours and the large VTOL drone was only affected 2% of the hours. Summer months were more impacted than other seasons in this location.

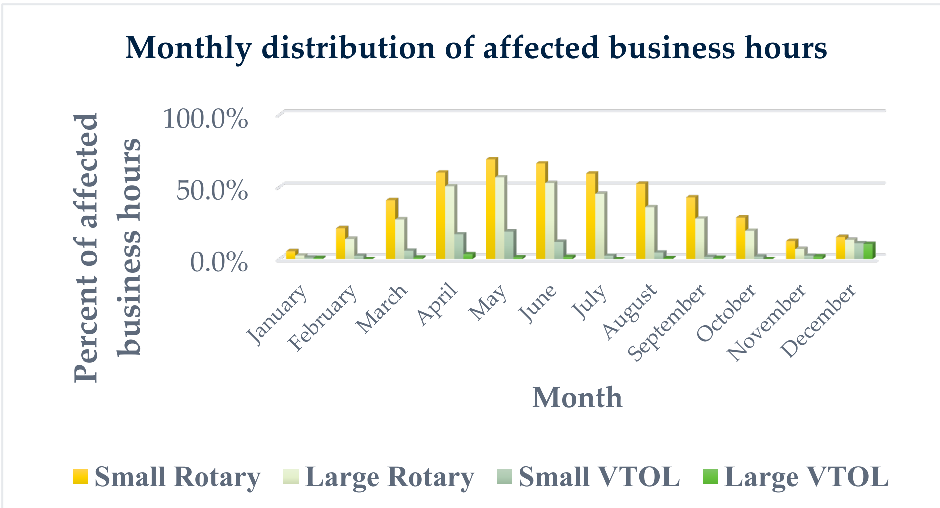

Figure I.1.5.3 Distribution of business hours affected by weather by drone type.

We also studied deploying a mixed fleet of ground vehicles and aerial drones for time-sensitive product delivery. In this business scenario, products are delivered directly by both aerial drones and ground vehicles from a business provider's location to the customers' locations. This mixed fleet of drones and ground vehicles is controlled by the business provider and all the drones and ground vehicles are stationed at the provider's location (depot). In this modeling scenario, each drone and ground vehicle carry only one package on each trip. Ground vehicles are used to deliver packages that cannot be delivered by drones due to battery energy and package weight capacity limitations. Similarly, ground vehicles would be used to perform all deliveries when weather limits drone flights or when there are zones where flights would not be allowed.

The project developed a mixed-integer programming optimization model that explicitly models the operating limitations (e.g., delivering products by either drone or ground vehicle, time window, battery replacement, number of packages in each trip) of this mixed-fleet business scenario and provides the optimal drone and ground vehicle routing and scheduling that minimizes the required number of drones and ground vehicles, total energy consumption, and the required number of drone battery replacements. We tested the optimization model using the one-hour spatio-temporal prepared-food delivery data based in the San Francisco Bay Area, California as described in previous project reviews. This analysis used a full set of 207 deliveries—several of which were excluded from previous analysis due to their longer distances from the depot.

The project again tested this mixed-fleet deployment model for three different types of drones— the large rotary, the small rotary, and the large VTOL— as well as three different types of ground vehicles. Table I.1.5.2 shows the variation in the required fleet size (i.e., the required number of drones and ground vehicles), total energy consumption, and the required number of additional batteries based on the drone type used. We see that using the small rotary drones requires the largest number of ground vehicles, whereas the fixed-wing VTOL does not require any ground vehicle for delivering the 207 customer orders in an hour. This is because the small rotary drone has the least battery capacity and thus has the least delivery range. On the other hand, fixed-wing VTOL has the largest package-weight carrying capacity and the longest range among all three drone types. Therefore, using a fleet of small rotary drones requires the largest number of ground vehicles and therefore the largest total energy consumption to deliver all packages. The fixed-wing VTOL consumes higher energy than the small rotary drones, but using a fleet of fixed-wing VTOL drones results in a smaller total energy consumption than using rotary drones as it removes the need of using ground vehicles.

Table I.1.5.2 Comparison of the Required Fleet Size, Energy Consumption, and Required Number of Batteries for Different Types of Drones

Drone types	Number of deliveries served by drones	Number of deliveries served by ground vehicles	Total energy consumed by drones (kWh)	Total energy consumed by ground vehicles (kWh)	Required number of drones	Required number of additional batteries	Required number of ground vehicles
Small Rotary	58	149	4.6	2107.2	20	23	66
Large Rotary	138	69	32.8	1609.3	44	40	44
Fixed-wing VTOL	207	0	71.4	0	64	18	0

Table I.1.5.3 shows the energy consumption among the three different types of drones and a ground vehicle for the same number of delivery locations (i.e., 58 deliveries that can be served by the small rotary drones). We see that the small rotary drone is the most energy-efficient among all the drones and vehicles, when considering the nearest 58 deliveries within the range of small rotary drones. Table I.1.5.3 also demonstrates the number of gallons of gasoline saved due to using different types of drones instead of ground vehicles.

Table I.1.5.3 Comparison of energy consumption, required fleet size, and delivery time among ground vehicles and drones.

Vehicle types	Total energy consumption (kWh)	Required number of vehicles	Total delivery time (minutes)	Number of gallons of gasoline saved using drones
Small Rotary	4.6	20	1070.7	9.9
Large Rotary	12.6	16	1025.7	9.6
Fixed-wing VTOL	14.9	14	752.4	9.5
Ground vehicle (Hyundai Accent 2022)	337.7	18	1548.2	-

When the project examined the effect of the different weather limitations as described above, the analysis demonstrated the increase in the total energy used in a mixed fleet by not being able to use drones for delivery during poor weather conditions. The analysis looked at the business hours impact in different months, using the ground-only fleet in those hours that drones could not operate and compared it to a baseline of the total energy consumption of the mixed fleet under normal conditions. Table I.1.5.4 shows the results based on each type of drone. The total energy consumed is the largest for the small rotary fleet, while the percentage increase in total energy consumption is the highest (e.g., 60% for yearly data) for the large VTOL drones. This is because there is no need of using ground vehicles with large VTOL in the mixed fleet under normal weather conditions, resulting in a significant percentage increase in energy consumption due to using ground vehicles under the adverse weather conditions.

Table I.1.5.4 – Impacts of weather limitations on fleet energy

Drone types	Percent of affected business hours	Yearly total energy consumption in kwh (ground vehicle fleet + mixed fleet)	Percent increase in energy consumption from the baseline (mixed fleet)
Small rotary	40%	10441996	6.3%
Large rotary	30%	8745868	14.5%
Small VTOL	7%	8823641	2.1%
Large VTOL	2%	531584	60.0%

The project also analyzed the effects of using a delivery circuit where each ground vehicle could deliver multiple packages in a route based on a delivery time-window, they found a significant reduction in the number of ground vehicles needed but a strong dependence on the delivery window size. The results shown here, however, are based on single deliveries per air or ground delivery.

In addition to ongoing analysis of the impacts of drone deliveries, the project began to develop a public-facing tool for using the tools and optimization techniques that have been developed as part of this drone energy project so far. The base-code of our developed software "Optimization Models for Drone Deployment" has been refactored and prepared to interface with external tools. It is anticipated that there will be three phases of a drone delivery energy calculator tool (Component Integration, Route Systems, and Route Enhancements) and two phases of a fleet calculator tool (Delivery Routines and Delivery Methods.) Final tools will be available to interested industry partners as well as the general public.

Conclusions

This work has shown that the use of drones for delivery of goods could have significant impact on the energy needed for localized delivery. It promises to improve the speed of delivery and reduce the energy needed to perform certain classes of deliveries. However, our research has shown that weather can have a large impact on how drones are used for deliveries. Most practical delivery systems will require a mixed fleet of air and ground vehicles to offer a consistent delivery solution. Choosing the right drone for the environment of the location will have a large impact on the overall energy and effectiveness of the system as a whole.

Acknowledgements

Tanveer Bhuiyan from the University of Texas at San Antonio has provided invaluable expertise and effort as a partner in creating optimization models and evaluation of results. Rohit Mendadhala from the Idaho National Laboratory has been a key team member. Mathew Balderree provided support as INL's chief UAV pilot. Inigo Timermans provided support on efforts from ANL. Industry partners from Spright, Interpath Labs, and Wing have provided invaluable support and insight.

The project also wishes to thank Avi Mersky from the Department of Energy for helping us to continuously improve throughout the year.

I.1.6 BEAM CORE (National Renewable Energy Laboratory, Lawrence Berkeley National Laboratory)

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Project Introduction

Starting in 2016, researchers at Lawrence Berkeley National Laboratory (LBNL), along with collaborators from NREL, embarked upon an ambitious mission: start from scratch to build an open-source, highly refined, agent-based regional transportation model for the San Francisco Bay Area accommodating a wide array of emerging and innovative transportation technologies and service models.

That model, known as Behavior, Energy, Autonomy, Mobility (BEAM), specializes in behavioral realism, capturing a comprehensive set of traditional and advanced transportation modes. BEAM integrates with cutting edge tools developed at NREL, including the Automotive Deployment Options Projection Tool (ADOPT), the Future Automotive Systems Technology Simulator (FASTSim), and the Route Energy Prediction Model (RouteE), which enable BEAM to simulate a comprehensive set of emerging vehicle innovations, such as electrification and automation, with highly resolved modeling of market penetration, technology evolution, and energy implications of these advanced vehicle technologies. For within-day transportation system modeling, BEAM employs an asynchronous actor-based software architecture—a parallelizable approach to routing and scheduling trips—enabling computationally tractable, dynamic, and time-dependent interactions of agents to ensure realism and internal consistency. BEAM is designed to resolve a set of "markets" for finite resources (road space, transit vehicle capacity, TNC fleet size, etc.) to bring supply and demand into equilibrium. Integration with an agent-based land use model, UrbanSim, enables a wide array of policy and scenario analyses focused on short-, medium-, and long-term impacts of emerging transportation technologies and service models, as well as transportation system design and land-use planning scenarios. This integration between BEAM, ADOPT, FASTSim, RouteE, and UrbanSim was previously referred to as the BEAM-centric SMART Mobility Workflow.

In FY 2021, LBNL, NREL, and UrbanSim team-members embarked upon a three-year project to extend development of the next generation of this integrated modeling framework by increasing the integration of sub-models, improving simulation capability, and enhancing computational performance, and demonstrates these extensions with a range of applications. The suite of integrated models is now known collectively as the BEAM Comprehensive Regional Evaluator, or BEAM CORE.

Objectives

BEAM CORE was organized around several objectives. The primary objective was to develop new capabilities that would strengthen BEAM CORE's specialization in long-term scenario analyses with dynamic and nuanced realism in regional population and economic behavioral evolution, thereby enabling BEAM CORE to answer a wider set of questions and increase its value to a wider set of stakeholders. This first objective was designed to take the model's ability to simulate realistic behaviors of individual travelers and freight/delivery actors to a new level, by integrating into BEAM CORE three new modules: Freight Activity Mobility Simulator (FAMOS), which enables modeling of freight delivery, generation of freight demand (including e-commerce demand), delivery planning, and delivery activity in the transportation system; Demographic Microsimulation (DEMOS), which simulates the lifecycle evolution of households; and Automobile and Technology Lifecycle-Based Assignment (ATLAS), a new vehicle transaction and technology adoption model, which makes vehicle and technology ownership decisions of households sensitive to lifecycle phases and related dynamics. ATLAS, which focuses on household-specific vehicle allocation and decisions, integrates with the existing ADOPT model, which captures how emerging vehicle technologies mature and penetrate into the market.

Complementary to the first objective are the second and third objectives, which focused on scaling application of the model. Specifically, the second objective has been to increase integration, automation, and improve algorithms, resulting in faster run times and more efficiency, enabling more ambitious scenario analyses and wider applicability. This increased automation and efficiency has resulted in significantly decreased run times and the ability to seamlessly run multi-year simulations in an automated loop. The third objective involved scaling deployment to new regions. BEAM CORE is currently implemented in some form in the San Francisco Bay Area; Detroit, Michigan; Austin, Texas; and New York City regions. Over the course of the project, the objective was to expand to a number of new regions. This objective proved difficult to implement as intended; however, the first phase of deployment to the Puget Sound region around Seattle, Washington is complete.

The fourth and final objective was to develop tools and disseminate actionable insights into the hands of stakeholders. The work on BEAM CORE during this three-year research phase was highly informed and guided by stakeholder input and has culminated in both a highly detailed mesoscopic modeling system as well as stakeholder engagement on actionable findings facilitated by the BEAM CORE Application and Collaboration Tool (ACT) platform. The objective was to have a series of reports and presentations prepared to document critical insights that can only be gleaned from such a comprehensive integrated modeling environment. A comprehensive set of sensitivity analyses was conducted to capture the marginal impacts of the individual levers that shift critical outcomes in the transportation system, as well as deep-dive analyses focused on specific critical issues identified by stakeholders.

Approach

BEAM CORE's integrated model configuration and structure is depicted in Figure I.1.6.1. BEAM CORE development has been organized into four tasks: (1) Enhanced Performance and Deployment - shortening run times through increased automation and connectivity between model components; enhancing key components; increasing efficiency of core algorithms; and deploying BEAM CORE. (2) New Capabilities - simulation of curb management and transit system design; ATLAS household vehicle fleet, usage, ownership, and technology adoption simulator; DEMOS model for demographic evolution of the synthetic population. (3) New Freight Capabilities - freight modeling capabilities that simulate freight activities, including decisions made by firms, shippers, and end-consumers, and integrating these into BEAM CORE. The freight modeling (FAMOS) will include both near-term freight generation and operation capabilities (which includes SynthFirm, FRISM [Freight Integrated Simulation Model], and BEAM-Freight), and capabilities to generate long-term/multi-year simulations of freight scenarios. (4) Application and Outreach - concerted stakeholder engagement; design and execution of scenarios and sensitivity analyses to run through BEAM CORE; design and development of BEAM CORE ACT; and deep-dive analyses of key research topics to generate actionable insights from BEAM CORE.

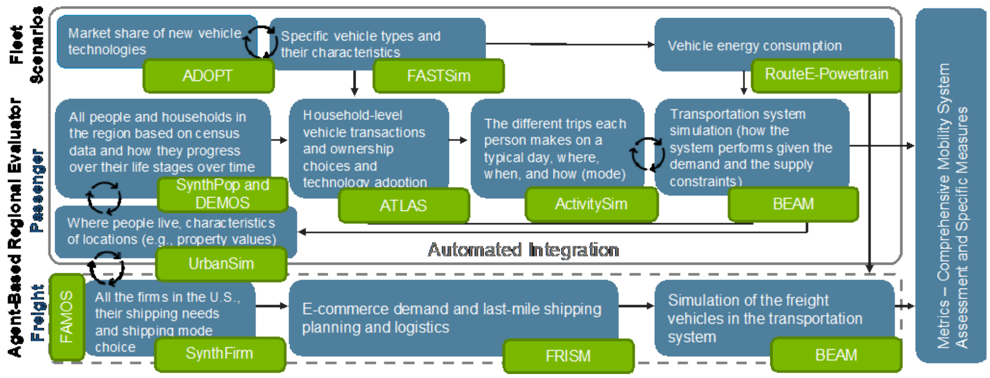

Figure I.1.6.1 BEAM CORE integrated model structure

Results

The full BEAM CORE suite of modules covering a wide range of new capabilities have been developed and implemented, in various combinations, in several regions in the U.S. over the course of SMART 2.0. Several modules in BEAM CORE were developed from scratch over the course of SMART 2.0, including DEMOS, ATLAS, and all of the FAMOS modules. That model development work has been completed this fiscal year. All modules in Figure I.1.6.1 have been integrated, calibrated, and validated in our San Francisco Bay Area implementation. In addition, all modules other than ATLAS have been calibrated and validated in the Austin region implementation. Finally, an implementation in Seattle is underway, with initial calibration completed for UrbanSim, SynthPop, ActivitySim and BEAM (noting that ADOPT, FASTSim and RouteE can be utilized in Seattle as is, or more refined region-specific vehicle scenarios can be established).

The BEAM CORE project developed and disseminated numerous products this fiscal year. Results from four Deep Dive studies using BEAM CORE were presented during the SMART Mobility 2.0 Webinar Series: a study on transit expansion projects in the Bay Area; an analysis of the potential impacts of more ridehail fleets, with larger fleet sizes and lower prices, in the Bay Area; the impact of zero emission vehicles, consolidated delivery, and increased e-commerce demand on freight energy consumption in the Austin Texas region; and the impact of technology progress as well as policies (including mandates, tax credits, and rebates) on the penetration of zero emission light-duty vehicles in the Bay Area. Several of these studies included an analysis of distributional outcomes in the population and equity considerations. Additional results on income-based cordon pricing, telecommuting, and additional transit expansion and freight results were presented during the last of two stakeholder workshops showcasing BEAM CORE.

Example results from each of the SMART Mobility 2.0 Webinar presentations are presented below. Each example set of results were selected to showcase the kind of analysis enabled by an integrated and disaggregated agent-based model such as BEAM CORE that cannot be generated by more traditional travel demand models. For example, in Figure I.1.6.2 we present how implementation of four new transit projects in the Bay Area might shift the travel mode of individuals using the new projects (left-hand panel). This ability to examine the change in behavior of individuals is a strength of an agent-based model such as BEAM CORE. Similarly, showing impacts disaggregated by population subgroups is something readily enabled by an agent-based modeling framework like BEAM CORE. For example, the right-hand side of Figure I.1.6.2 indicates the median income of the agents that utilized the new transit projects in the simulation.

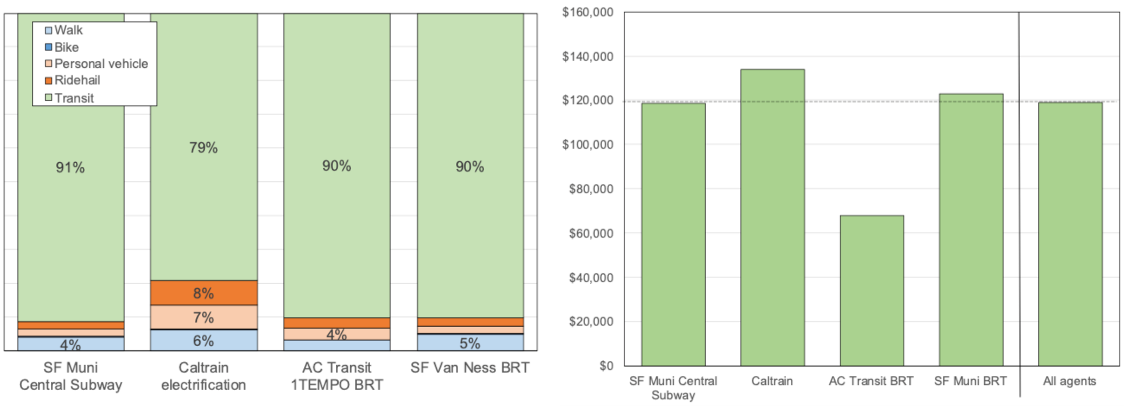

Figure I.1.6.2 Simulated transit expansion in the San Francisco Bay area

Figure I.1.6.3 demonstrates how BEAM CORE can be used to understand the non-linear impacts that can arise from an integrated simulation of multiple interconnected networks. In this case, the left-hand panel shows how, as the price of ridehail declines, the share of pooled ridehail initially increases, but eventually decreases, for at least two reasons: more affordable solo ridehail becomes more competitive with pooled ridehail, and demand for a fixed number of ridehail vehicles increases the cost of coordinating and matching pooled ride requests, thereby increasing wait times for pooled ridehail and making it less desirable.

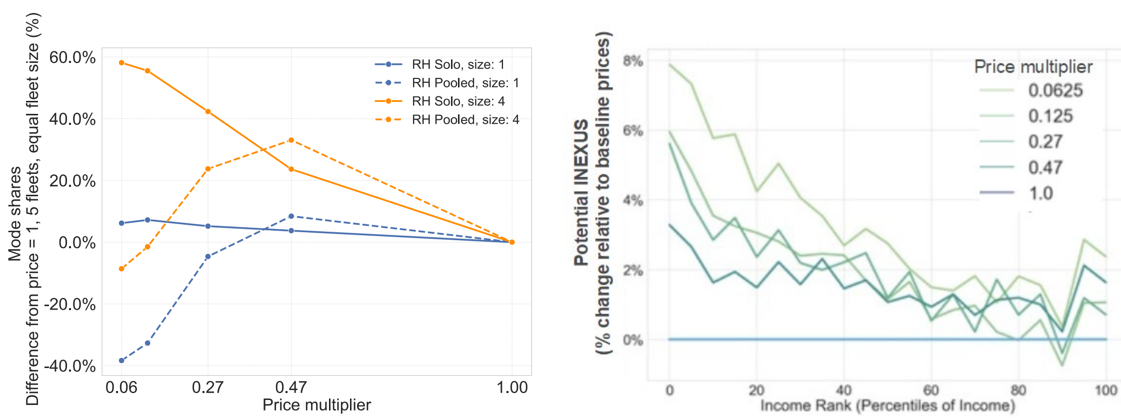

Figure I.1.6.3 Scenario analyses of ridehail price and fleet composition in the San Francisco Bay area

The right-hand panel of Figure I.1.6.3 shows again the power of an agent-based simulation such as BEAM CORE to demonstrate the heterogeneous impact of different scenarios across different population groups. Here the accessibility impacts (measured using the Potential INEXUS accessibility metric) are shown by household income decile, demonstrating that less expensive ridehail disproportionately benefits lower income travelers.

Figure I.1.6.4 shows the impact of a technology success scenario alone on ZEV penetration and use for freight (left-hand panel), contrasted with a scenario combining technology success and financial incentives (extended rebates and relative fuel pricing favorable to ZEV freight and delivery technology). The results demonstrate that technology success alone has a limited impact on conversion of vehicles and VMT to ZEV technology, resulting in a 36% reduction in energy consumption by 2050, while additional market and policy factors favorable to ZEVs significantly increase the penetration and use of ZEVs in freight and delivery activity, resulting in a 53% reduction in energy use by 2050. In both cases, ZEVs are used disproportionately more than diesel vehicles (demonstrated by the higher ZEV VMT share than fleet share).

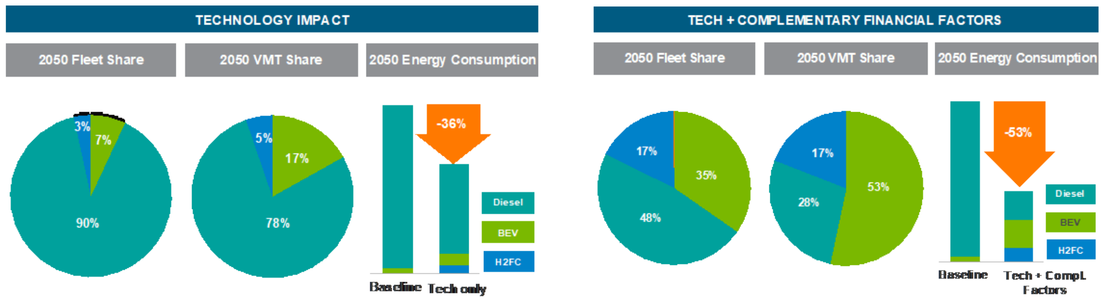

Figure I.1.6.4 Scenario analyses of zero emission freight and delivery technology and complementary financial factors in Austin, Texas

Finally, Figure I.1.6.5 shows the impact of ZEV LDV technology success and policy (ZEV mandate) in changing the turnover of the household LDV fleet from internal combustion engines (ICEs) to ZEV. If battery prices drop based on the projected technology success trajectory, ZEVs are modeled to penetrate 40% of the fleet by 2037, while stagnating battery prices could delay ZEV penetration by six years. Alternately, technology success coupled with the mandate can accelerate ZEV penetration by four years. Analysis of incentives indicate that rebates, more so than tax credits alone, or the absence of any financial purchase incentives, can significantly improve the distribution of ZEVs across household income levels.

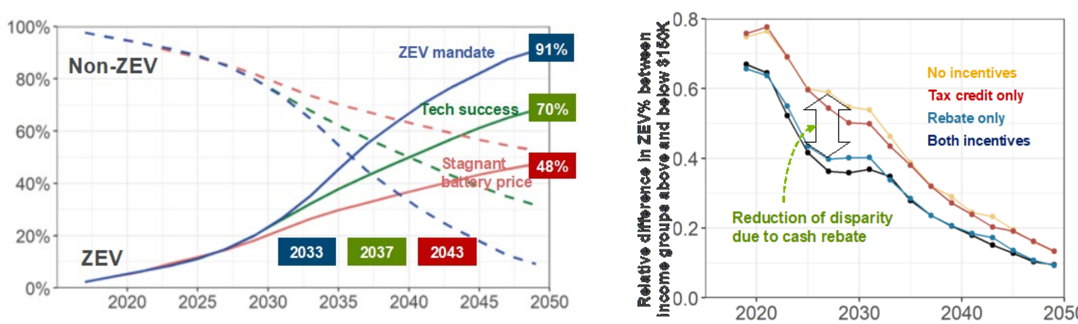

Figure I.1.6.5 Scenario analyses zero emission light duty vehicle technology and equity impacts of incentives in the San Francisco Bay area

Conclusions

The BEAM CORE capabilities under SMART Mobility 2.0 have been deployed with great success. These new capabilities have been used to generate a wide range of nuanced analyses in multiple regions. Results from this work have been, and will continue to be, disseminated in a range of ways: multiple webinars, such as those presented as a part of the SMART Mobility 2.0 webinar series discussed above, as well as others; in over a dozen Transportation Research Board or other conference presentations given or accepted; and in three rounds of workshops with stakeholders. In addition, the BEAM CORE team is developing journal publications documenting the technical components of the BEAM CORE modules, as well as showcasing the results including, but not limited to, the above-described analyses. Many of these publications are already published or under review (see the publications list), with more to be finalized and submitted shortly. Finally, the BEAM CORE ACT tool, a web interface designed to explore results from BEAM CORE sensitivity analyses, has been developed and made available to BEAM CORE stakeholders to explore and provide feedback. The tool has been populated with a range of sensitivity analyses on specific scenario “levers” in BEAM CORE, including those impacting transit system design, ridehail system operations and supply, and modal preferences and incentives.

Key Publications

1. Bang, H., Holden, J., Mahbub, A. M., Gonder, J., & Malikopoulos, A. A. (2023). Exploring Microsimulation Process for Energy Impact Evaluation of Connected and Automated Vehicles. In 2023 Transportation Research Board Annual Meeting (No. TRBAM-23-00998). https://trid.trb.org/view/2117808

2. Jin, L., Lazar, A., Brown, C., Sun, B., Garikapati, V., Ravulaparthy, S., ... & Spurlock, C. A. (2022). What Makes You Hold on to That Old Car? Joint Insights from Machine Learning and Multinomial Logit on Vehicle-Level Transaction Decisions. *Frontiers in Future Transportation*, 3, 894654. https://doi.org/10.3389/ffutr.2022.894654

3. Laarabi, H., Needell, Z., Waraich, R., Poliziani, C., & Wenzel, T. (2023). BEAM: The Modeling Framework for Behavior, Energy, Autonomy & Mobility. *arXiv preprint arXiv:2308.02073*. https://arxiv.org/abs/2308.02073

4. Lazar, A., Jin, L., Brown, C., Spurlock, C. A., Sim, A., & Wu, K. (2021, December). Performance of the Gold Standard and Machine Learning in Predicting Vehicle Transactions. In 2021 IEEE International Conference on Big Data (Big Data) (pp. 3700-3704). IEEE. https://doi.org/10.1109/BigData52589.2021.9671286

5. Poliziani, C., Hsueh, G., Czerwinski, D., Wenzel, T., Needell, Z., Laarabi, H., ... & Rupi, F. (2023). Micro Transit Simulation of On-Demand Shuttles Based on Transit Data for First-and Last-Mile Connection. *ISPRS International Journal of Geo-Information*, 12(4), 177. https://doi.org/10.3390/ijgi12040177

Under Review:

6. Goulias, K., Xiao, J., Ravulaparthy, S., Sharda, S. (Under Review – Revise and resubmit *Energy Policy*) Microsimulation Scenarios of Autonomous Vehicle Adoption and Impacts on Annual Vehicle Miles Travelled (VMT) and Greenhouse Gas Emissions (GHGs) in California.

7. Jin, L., Jackson C., Wang, Y., Chen, Q., Ho, T., Spurlock, C.A., …, Caicedo, J. (Under Review) Development and Application of a Household Vehicle Fleet Micro-simulator to Assess the Impact of Technology Progress and Clean Vehicle Policies on Fleet Turnover and Equity.

8. Spurlock, C.A., Bouzaghrane, M.A., Brooker, A., Caicedo, J., Garikapati, V., Gonder, J., ..., Xu, X. (Under Review) Behavior, Energy, Autonomy & Mobility Comprehensive Regional Evaluator: Overview, calibration and validation summary of an agent-based integrated regional transportation modeling workflow.

9. Sun, B., Sharda, S., Garikapati, V., Bouzharhane, M.A., Caicedo, J., Ravulaparthy, …, Waddell, P. (Under Review). Demographic Microsimulator for Integrated Urban Systems: Adapting Panel Survey of Income Dynamics to Capture the Continuum of Life.

10. Wenzel, T. (Under Review). Net change in energy use from ridehail service in five California regions.

11. Xiao, J., Goulias, K., Sharda, S., Ravulaparthy, S. (Under Review) Microsimulation Scenarios of Autonomous Vehicle Adoption and Impacts on VMT and GHGs Emission in California.

12. Xu, X., Yang, H.C., Jeong, K., Bui, W., Ravulaparthy, S., Laarabi, H., Needell, Z., Spurlock, C.A. (Under Review). Teaching Freight Mode Choice Models New Tricks Using Interpretable Machine.

13. Xu, X., Yang, H.C., Jeong, K., Ravulaparthy, S., Laarabi, H., Needell, Z., Spurlock, C.A. (Under Review). A Large-Scale Agent-based Model for Business-to-business Freight Demand Simulation.

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I.1.7 Metrics for Assessing the Impacts of Energy-Efficient Mobility Systems (National Renewable Energy Laboratory; Lawrence Berkeley National Laboratory)

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Project Funding: $595,000 DOE share: $595,000 Non-DOE share: $0

Project Introduction

While the development of the MEP metric served the need of assessing various SMART Workflow scenario runs in SMART 1.0, some gaps still remain, motivating a need to advance the metric. Such gaps include computing a MEP score that reflects the socio-demographic characteristics and choices of an individual, and other methodological enhancements that were discussed during the course of SMART 1.0. This project aims to build on the current strengths of the MEP metric and enhance its capabilities to enable answering an even wider range of questions associated with emerging transportation alternatives. To continue the efforts in advancing the robustness of the MEP metric, the project team plans to tackle four broad areas, namely:

1. Enhancements to the existing MEP methodology and calculation procedure
2. Development of MEP metrics disaggregated by individual characteristics
3. Development of a MEP visualization platform
4. Collaborating with state departments of transportation (DOTs)

Objectives

The objective of this project is to build on the strengths of the existing MEP metric as well as develop complementary aspects to the current MEP metric, so that mobility and energy impacts of existing, and future transportation system can be evaluated using a suite of geographically, and demographically diverse metrics. The end goal of this project is to develop a robust set of metrics to quantify the effectiveness of transportation options in connecting people to opportunities and places. The primary outcome from this project is an evolved version of the MEP calculation methodology that is matured and tightly integrated with the SMART Mobility Workflow modeling process. Proposed enhancements (and additional metrics) will enable MEP to add robustness to its quantification of mobility and energy impacts of evolving transportation system scenarios, and to connect the impact of broader VTO investments to holistic mobility and energy outcomes under these scenarios. Details of various tasks in this project are detailed below.

Task 1

- Develop empirical coefficients for cost, energy, and time parameters that can be published as standards, and used in developing the baseline MEP metrics.
- Enhance the MEP methodology to account for multimodal trips (e.g., travel shed reachable by a combination of e-scooter and transit modes within ten minutes of travel).
- Explore accommodation of additional weighting factors such as emissions, infrastructure quality, and safety (alongside existing, time, energy, and cost parameters) in MEP computation.
- Extend the existing methodology to i) incorporate parking wait times into the driving mode (at the link level); and ii) move from a static MEP quantification to a time-of-day based quantification.

Task 2

- Customize the existing MEP metric to reflect socio-demographic characteristics of individuals.
- Develop an individual-level metric, the Individual Experienced Utility-Based Synthesis (INEXUS), from outputs of the BEAM CORE agent-based model capturing the weighted valuation of the agents' experience over multiple dimensions resulting from the realized set of choices made by the agent given the scenario conditions.

Task 3: Develop an interactive web-tool to compare and contrast MEP scores from various scenarios. The tool can be viewed from anywhere and will offer the flexibility to choose specific scenarios for side-by-side comparisons.

Task 4: Engage in collaborations with Delaware Department of Transportation, Florida Department of Transportation, and Colorado Department of Transportation to integrate MEP calculations into travel demand models developed by respective DOTs.

Approach

Task 1

Finalization of the Multimodal Routing Methodology: MEP calculation is carried out at the resolution of a square kilometer (sq.km) pixel, by first quantifying the extent of area that can be reached from a given location within a given amount of travel time (e.g., 10, 20, 30 or 40 minutes). The resulting spatial extent is called an 'isochrone'. In the first version of the MEP metric (MEP 1.0), NREL researchers leveraged off-the-shelf routing packages to conduct reachability searchers which are unimodal in nature. While these packages provide a great starting point to conduct reachability searches, they came with some limitations such as: 1) lack of flexibility in representing modal transitions and delays, and 2) limited scaling capability toward parallel execution. To address these challenges, the MEP team has developed MEP 2.0, a revised version of the original MEP 1.0 software, employing a multimodal reachability search. The multimodal solution allows for dynamic cost estimates and mode transitions across a region, which leads to more realistic estimates of opportunity access, while also facilitating parallel search capabilities to reduce run times. To demonstrate the capabilities of the new multimodal search and isochrone generation algorithm, two scenarios (which were previously infeasible) were tested:

- An exploration of *dynamic parking delays* in drive-mode travel (with no parking delay as the baseline),
- A study of the impact of various *feeder modes* on transit travel (with transit-walk as the baseline).

Simulated data from LBNL's BEAM model from the San Francisco Bay Area was used to conduct these experiments.

Incorporating Level of Traffic Stress (LTS) in Bike MEP Calculations: LTS is an approach that quantifies the amount of discomfort people experience when they bicycle/walk close to traffic [1]. The addition of LTS in MEP computation helps account for infrastructure suitability for safe biking and walking and is expected to provide insights on how best to prioritize locations for future infrastructure investments that minimize traffic stress. To reflect LTS in MEP calculations, the LTS of road segments were determined based on functional class, speed limit and directionality (one-way or two-way) of the segment. Specifically, four levels of LTS are defined: (a) LTS 1 – Low traffic stress and suitable for all cyclists (including children); (b) LTS 2 –little traffic stress but requires more attention (especially for children); (c) LTS 3 – moderate traffic stress-suitable for confident cyclists; and (d) LTS 4 – high traffic stress (or discomfort while bicycling). To show the impact of LTS on bike access, MEP scores for computed for baseline (i.e., without LTS) and LTS scenarios. For preliminary testing, MEP scores were calculated for a small study area in the Denver metropolitan region.

Task 2

Methodologies of both the socio-demographic MEP (**SD-MEP**) metric as well as the **INEXUS** suite of metrics were finalized in FY 2023. Both the methodologies were documented in technical papers which were presented at the 102nd Transportation Research Board (TRB) Annual Meeting and are currently in the journal review process.

Task 3

EV Scenario Analysis Capability Implemented in the MEP Dashboard: In FY 2022, a web visualization dashboard was developed using the R-Shiny platform to display static MEP scores. The dashboard was showcased to various DOT, industry, and academic stakeholders. While the feedback to the dashboard was positive in general, several stakeholders felt that the ‘static’ nature of the dashboard limits the types of analyses users can conduct. Responding to this feedback, in FY 2023, an EV scenario evaluation capability was developed and integrated into the dashboard. Through the EV scenario evaluation tab, users can select the level of EV penetration in their city and visualize the resulting MEP scores. Level of EV penetration is reflected in MEP calculations through the energy intensity input (in kWh/passenger-mile) for drive and transit modes.

Task 4

Leveraging MEP for Quantifying the Impacts of Infrastructural Investments: Aspiring smart cities are wrestling with questions such as: How does mobility impact a person’s quality of life? Would people make different travel choices if they were presented with better information about their mobility options? The ability to quantify the quality of mobility at a given location is the first step toward answering these questions. The MEP metric provides an avenue to not only measure the quality of mobility at a specific location in its current configuration, but also to test how various technological advancements and infrastructure investments impact the mobility of that location over time. In FY 2023, the MEP metric has been leveraged by various state DOTs to evaluate the impacts of infrastructural investments. In a project with the Florida Department of Transportation, MEP scores were computed for bike lane expansion as well as transit service enhancement (and electrification) scenarios in Miami, Florida. Similarly, for a project done in collaboration with the Colorado Department of Transportation, MEP scores were computed for “hypothetical” freeway expansion, and transit service enhancement scenarios.

Results

Finalization of the Multimodal Routing Methodology: The new multimodal routing methodology is able to capture parking delays and access mode impacts quite well. Results for the full suite of scenarios, shown in

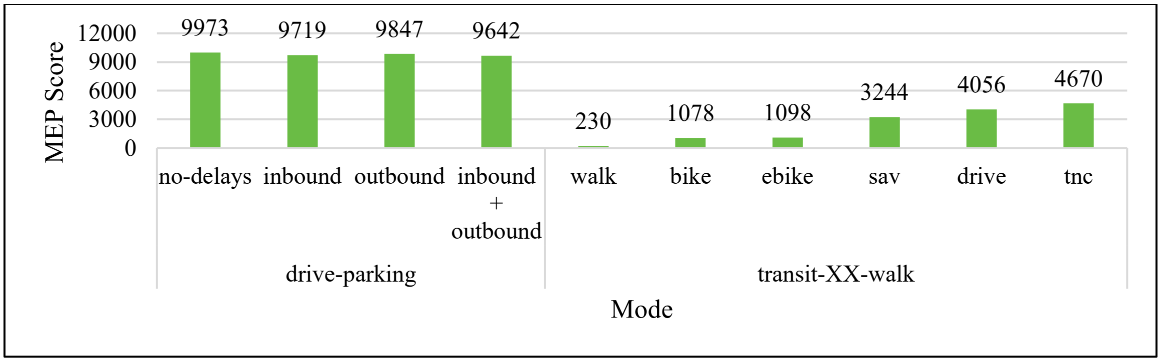

Figure I.1.7.1 demonstrate a marginal negative impact on accessibility (and MEP scores) from Figure I.1.7.1 MEP scores for various scenarios tested using the multimodal routing methodology

drive-mode delays and positive impacts on transit accessibility when faster travel options are used as feeder modes. In the drive-parking-inbound+outbound scenario, compared to baseline, a 3.3% decrease is observed in MEP scores when both inbound and outbound parking delays are imposed. The change in MEP scores is smaller given the median parking delays observed (at zonal level) in BEAM outputs are 2.79 and 4.09 minutes only. In the case of transit scenarios, with the use of TNC as the last-mile connection (transit-TNC-walk), overall MEP score increased 20 times compared to baseline (transit-walk). Interestingly, the scores in this scenario are greater than the one where drive mode is used as first mile last-mile connection because parking penalties are imposed at both origin and destination of the drive trip. In transit-sav-walk scenario, shared automated vehicle (sav) is considered as a feeder mode with a 15-minute wait time penalty, impacting accessibility scores significantly compared to transit-drive-walk and transit-tnc-walk scenarios.

Incorporating Level of Traffic Stress (LTS) in Bike MEP Calculations: The baseline bike MEP score for the study region (shown in Figure I.1.7.2) is 4.68. In the LTS scenario, the bike speeds are decreased by 25%, 50%, and 75% (from baseline) for segments categorized as LTS 2, LTS 3, and LTS 4, respectively. This reflects that biking and walking is undesirable or uncomfortable on links with higher LTS. The average speed remains unchanged for segments that are categorized as LTS 1 (3.1 mph for walking and 9.3 mph for biking). After incorporating LTS, the bike scores reduce to 2.17, which is a reduction of 53% from the baseline. Further, in the LTS scenario, the number of opportunities that can be accessed by biking decreased by about 50 percent, compared to baseline. Accounting for infrastructure availability (through LTS) helps paint a realistic picture of the level of access availed to bicyclists in the study region. Efforts are underway to leverage this framework to quantify the impacts of various infrastructure enhancements (i.e., implementation of dedicated bike lanes), and regulatory policies (i.e., traffic calming; sidewalk access) on the true level of access availed to electric bikes, and electric scooters.

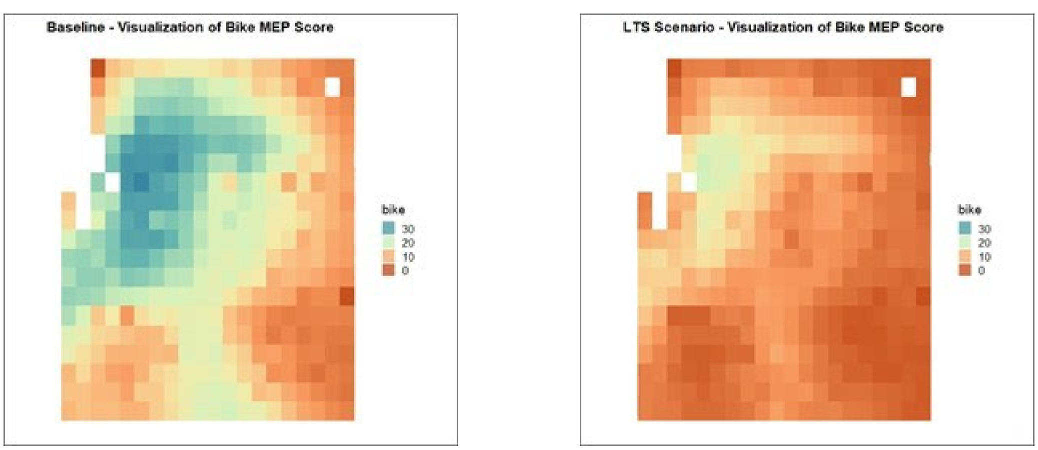

Figure I.1.7.2 Bike MEP scores for the study region for baseline (left) and LTS (right) scenarios

INEXUS: The pipeline for deriving the INEXUS from BEAM CORE outputs has been completed and INEXUS has been applied across a range of BEAM CORE studies. A journal article documenting and demonstrating the INEXUS metrics is under review at a journal following one round of reviewer comments and a resubmission. Example results demonstrate how the INEXUS can be used to both characterize the distribution of accessibility in the baseline or show how that distribution changes for different population groups under alternative scenarios (Figure I.1.7.3). Specifically, moving from baseline price to no-cost TNC results in a 33% improvement in the median Potential INEXUS for the lowest income decile compared to only 11.5% for the highest income decile.

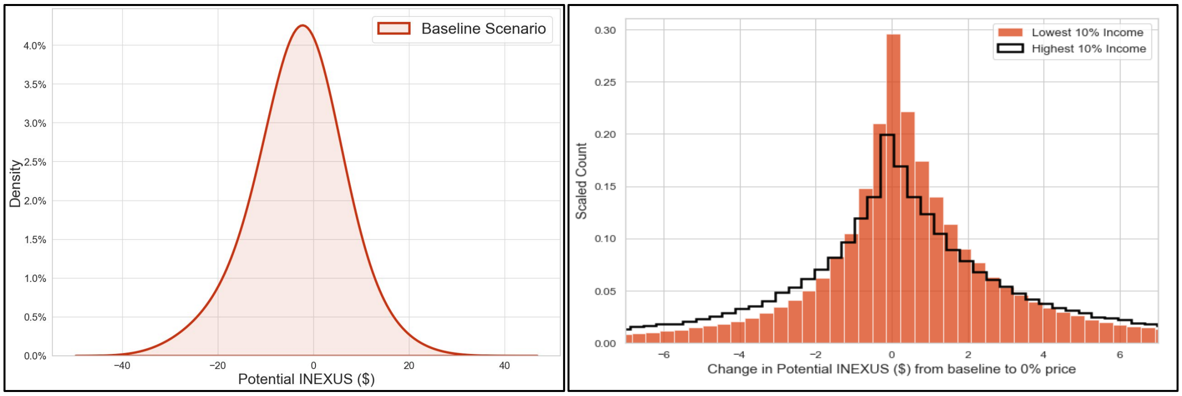

Figure I.1.7.3 Potential INEXUS distribution in the baseline scenario (left) and change in Potential INEXUS from the baseline for a scenario with no-cost TNC pricing for the highest and lowest income groups (right)

EV Scenario Analysis Capability Implemented in the MEP Dashboard: As seen in Figure I.1.7.4, users can select % EV adoption in their city using a slider. MEP scores will then be updated based on weighted average of energy intensity of EVs and internal combustion engine (ICE) vehicles pertaining to that scenario.

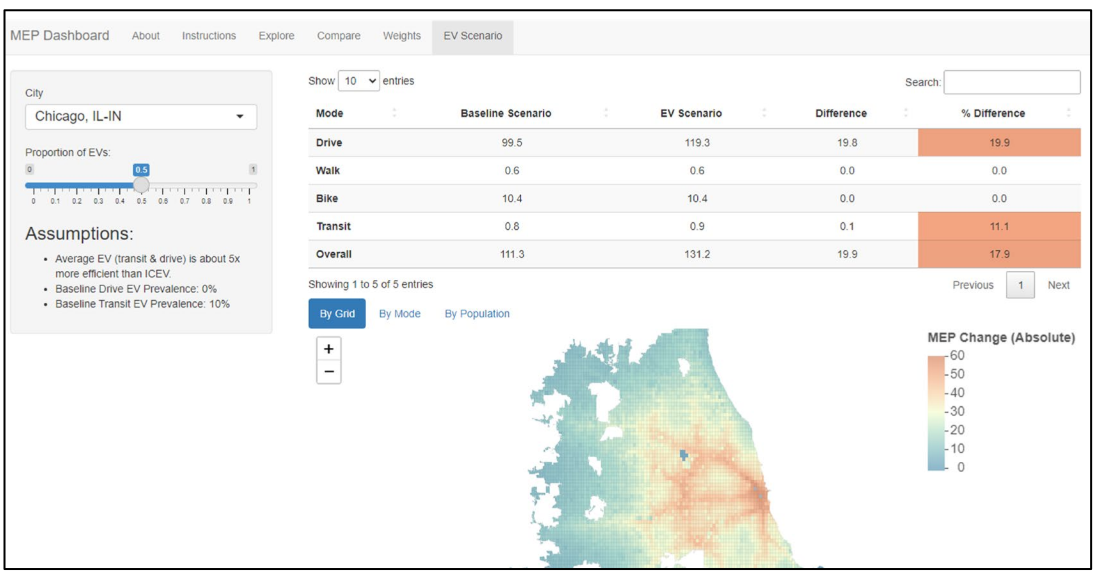

Figure I.1.7.4 EV scenario analysis capability in the MEP dashboard

The results are presented in the form of a table, a plot (showing difference in MEP values between the baseline and EV penetration scenarios) and also summary charts split by mode and population segment (not shown in the figure). Similar scenario analysis capabilities (such as change in fuel prices, or improvement in transit service) are being explored by the MEP team for possible integration into the dashboard.

Leveraging MEP for Quantifying the Impacts of Infrastructural Investments: The MEP team worked with researchers at Florida International University to compute MEP scores based on the outputs of the

Southeast Florida Regional Planning Model (SERPM) which is a four-step travel demand model, developed and managed by the Florida DOT. A few modifications were made to MEP calculation process in order to make it work with the aggregate outputs of the SERPM model. Once a baseline was established for the year 2015, a scenario was defined to evaluate the impacts of bike infrastructure enhancements (planned for the year 2045) in north, central and south corridors in Miami, Florida. A MEP analysis was carried out to quantify the increase in number of opportunities that would result from bike infrastructural enhancements proposed for each of these corridors. As seen from Table I.1.7.1, the North Corridor, despite having the least amount of bike lane-mile enhancements, had the greatest improvement in opportunity access per lane mile. The south and central corridors, despite the huge variation in the amount of infrastructural enhancements, led to roughly the same increase in opportunities per lane mile. Based on this finding, it would be prudent for the city authorities to take up the enhancement of the north corridor first, followed by the south and the central corridors.

Table I.1.7.1 Ten- and Twenty-Minute Opportunity Count/Lane Miles for the Proposed Bike Corridors

Location	2015 Opportunity Count per Grid/Total Lane Miles	2045 Opportunity Count per Grid/Total Lane Miles	Opportunity per Grid Difference	Lane Difference (in miles)	Opportunity Increment/Lane-Mile
North Corridor	68,590 opps 9.9 miles	88,987 opps 43.9 miles	41,923	34.0	1,233
Central Corridor	68,044 opps 114.1 miles	112,470 opps 260 miles	44,426	146	304
South Corridor	52,267 opps 25.9 miles	70,585 opps 84.6 miles	18,318	58.7	312

Conclusions

In FY 2023, the MEP team focused on finalizing all of the methodological and computational enhancements planned for the MEP metric as a part of SMART 2.0 research activities. Specifically, the team focused on integrating the multimodal routing methodology into MEP calculations (leading to a 16-fold reduction in run times) and incorporating LTS in walk and bike MEP calculations. Similarly, INEXUS and SD-MEP methodologies have been finalized and submitted for review in journal venues. Based on feedback received on the web visualization dashboard, the MEP implemented an EV scenario analysis capability through which users can select the percentage of EV penetration in their city and view the baseline vs. EV scenario MEP results. Through collaborations with Colorado, Delaware, and Florida DOTs the MEP team leveraged the MEP metric to evaluate the impact of various infrastructural investments. These collaboration also identified some aspects for improvement in the metric. Going forward, the MEP team plans to focus on 1) adopting open-source data for MEP calculations; 2) increasing interpretability of MEP scores; and 3) lowering the barrier for adoption of the metric through web-based sketch planning capabilities.

Key Publications

1. Hoehne, Christopher, Max Hanrahan, K. Shankari, and Venu Garikapati. "Mobility Energy Productivity and Equity: E-Bike Impacts for Low-Income Essential Workers in Denver." *Transportation Research Record* (2023).

2. Sharda, Shivam, Christopher Hoehne, Sailesh Acharya. Michael Allen, Venu Garikapati, Ambarish Nag, and Yantao Huang. Navigating the Urban Jungle: Evaluating the Impact of Infrastructure Policies on Energy-Efficient Access for Micro-Mobility. Selected for presentation at the 103rd TRB Annual Meeting.

3. Rezeaei, Nazanin, Annika Todd-Blick, K. Fujita, Natalie Popovich, Zachary Needell, Cristian Poliziani, Juan Caicedo, and C. Spurlock. Investigating Distributions of Transportation Accessibility through the Individual Experienced Utility-Based Synthesis Metric. In Review: *Journal of Transport Geography* (2023).

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1. Furth, Peter G., Maaza C. Mekuria, and Hilary Nixon. “Network connectivity for low-stress bicycling.” Transportation research record 2587, no. 1 (2016): 41-49.

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From the project team: The project team would like to extend their sincere thanks to the DOE leadership (Michael Berube; Jake Ward; Alexis Zubrow), and EEMS technology managers (previously Heather Croteau and Nadya Ally, and now Melissa Rossi) for their feedback on the development of this metric.

I.1.8 Micromobility Integrated Transit and Infrastructure for Efficiency (MITIE) (National Renewable Energy Laboratory)

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Project Introduction

Nearly omnipresent in many cities of all sizes across the United States, micromobility vehicles–e-scooters, manual bicycles, e-bicycles, and larger seated electric scooters–are notably missing from SMART research. This project aims to expand the spectrum of modes currently being researched within SMART by exploring micromobility as an important tool toward meeting energy-efficient mobility goals. It expands on findings from SMART 1.0 that revealed preferences to reduce transportation-related expenses through use of a network of mobility-as-a-service and other shared mobility options, and builds on findings from a 2019 Vehicle Technology Analysis Program funded micromobility project conducted by our team. We will explore multiple facets of micromobility, including behavior and decision-making, the integration of micromobility within transportation infrastructure, energy estimates, and operations. Guiding research questions include:

- What are the potential energy savings from low, medium, and high market penetration of micromobility (in passenger, multimodal, and freight domains)?
- Which scenarios for micromobility use and related enablement of increased public transit use should be modeled/considered in the SMART 2.0 Workflow?
- To what degree can micromobility supplement/complement transit system operations?
- What are people's preferences towards micromobility? How do preferences vary across various sociodemographic segments? How can this knowledge inform operations?
- What are optimal strategies to attain high user adoption and shift users toward more energy-efficient mode choices in terms of micromobility operation? How do these strategies affect energy savings, person-miles traveled, lifecycle energy use, and adoption rates?

These questions are addressed through applied research in five project emphasis areas:

1. Energy estimates of micromobility for Workflow scenarios: Expand and refine previous micromobility work to augment the Workflow approaches to modeling urban travel.
2. Multimodal connection with transit: Utilizing MEP tools to evaluate multimodal travel patterns enabled by micromobility, including assessing how to reduce barriers of inequity of access to mobility options and destinations.

3. Mode choice, induced demand, and infrastructure: Understanding the mode shift induced through micromobility to inform energy impact analysis.

4. Energy optimization of micromobility operations: Identification of micromobility operations parameters and development of operations scenarios to better understand present-day micromobility operations for integration into the Workflow, in partnership with BEAM and POLARIS modeling teams.

5. Micro-freight: Characterize the current state of micro-freight activities, including energy effects and geospatial analyses, to inform Workflow.

Objectives

Goals of this project are to establish fundamental micromobility research to inform efforts within EEMS, to provide baseline energy estimates, to cross-inform other SMART projects, and to provide data support for refinement of Workflow processes to better account for micromobility in system modeling and simulation.

Objectives:

1. A comprehensive set of micromobility scenarios to be integrated into Workflow scenarios.

2. Quantitative estimates of micromobility energy impacts for low, medium, and high adoption scenarios.

3. Analysis of interconnected transit/micromobility use to inform MEP-based approaches to reducing barriers and inequity of access to mobility and destinations.

4. Behavioral models of current and hypothetical micromobility modes and analysis of how instructive/supportive infrastructure affect induced demand.

5. Energy optimization estimates of micromobility operations, including in-area and co-optimization of charging strategies, automation for redistribution/charging, and infrastructure integration to inform mesoscale models and system-scale vehicle electrification models.

6. Quantitative energy estimation of micro-freight and factors changing micromobility adoption to inform Workflow application and overall impacts of new strategies enhancing system performance.

Approach

The approach to this project is through the research work delineated between several tasks designed to address specific objectives. These tasks include:

Task 1: Energy estimates of micromobility for Workflow scenarios – Develop micromobility trip replacement scenarios for integration into the Workflow, in partnership with BEAM and POLARIS modeling teams.

Task 2: Collection and analysis of trip-level data from micromobility services in multiple cities – Identify multimodal activity between micromobility, transit, and other modes to develop scenarios for trip replacement and multimodal activity enabled by micromobility, to inform POLARIS, BEAM models.

Task 3: Mode choice, induced demand, infrastructure – Produce FIF and mode-agnostic behavioral modules for micromobility adoption (including multiple behavioral factors and characteristics) for integration into Workflow to model future or anticipated micromobility implementations.

Task 4: Energy optimization of micromobility operations – Identification of micromobility operations parameters and development of operations scenarios to better understand present-day micromobility operations and improvement strategies for integration into the Workflow.

Task 4A: “Alternative” Use and Emerging Forms of Personal and Freight Mobility – Examine emerging forms of mobility including automated shuttles, scooters, and other personal mobility devices as well as emerging freight options including land-based drones, autonomous and other small delivery devices.

Task 5: Micro-freight – Characterize the current state of micro-freight activities, including energy effects and geospatial analyses, to inform Workflow.

Results

Task 1: Integration of micromobility into workflow modeling

BEAM Workflow: The MITIE team provided the BEAM team with refined micromobility scenarios to be run according to timing determined by the BEAM team. The mode choice model that considers the shared micromobility services will be tested as a scenario rather than integrating the model into the BEAM CORE workflow.

POLARIS Workflow: The shared-micromobility mode choice model has been shared with POLARIS modeling team which will be tested in existing POLARIS scenarios. Either the coefficients of the MITIE mode choice model will be directly adopted, or the relative coefficient magnitude ratio will be borrowed.

Energy estimates of private-ownership e-bike use

Expanding beyond shared micromobility energy estimates, a focus on energy estimates of private ownership e-bikes was developed, informed by earlier findings that e-bikes show high car replacement potential (see Figure I.1.8.1). Nationally, high adoption of e-bikes to replace viable car trips could save 6.6% of passenger travel energy, and at the city scale, energy savings are estimated at 7.5%, using Sacramento as an example. Personal e-bike data patterns show strong car replacement behavior potential.

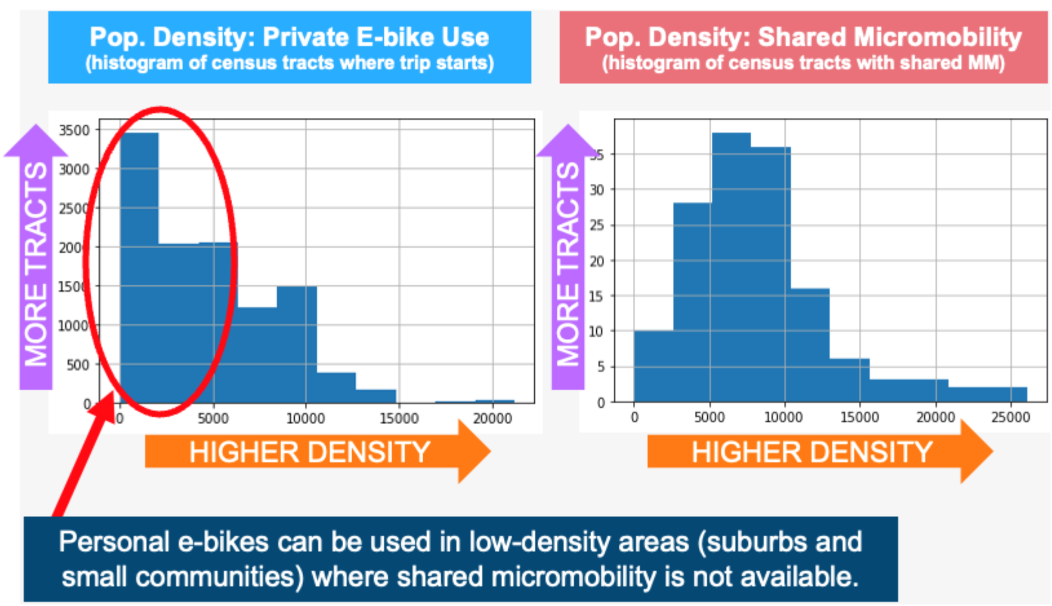

Figure I.1.8.1 E-bike use observed in different geographic settings through data collected from the Colorado Energy Office e-bike program

Task 2: Collection and analysis of trip-level data from micromobility services in multiple cities

Analyze micro-mobility trip data

The LBNL team continued work drafting a journal article summarizing the results of the analysis of micro-mobility trip data from dockless programs in 11 cities. The paper covers several findings related to the analysis of energy use of micromobility systems. The results provide insight on the rate of energy consumption by micromobility vehicles across different systems. Further work within the paper is using this information to model the trip and environmental attributes that contribute to energy use of use trips, which include trip distance, time, elevation, wind speed and others. The goal is to advance the completed draft to an academic journal for the purposes of results dissemination. This outcome depends on acceptance by the journal, but otherwise the completed draft will serve as a reported summary of research output from the project.

Calibration and validation with Workflow models
A report summarizing the incorporation of micromobility into the BEAM agent-based model was finalized, including enhancements made to more accurately simulate docked bikeshare in the San Francisco Bay Area using BEAM. The report includes final results from sensitivity analyses regarding number of bikes and docks, and cheaper and free bikeshare scenarios, as well as four scenarios that prohibit personal vehicle use for trips with origins and destinations within one-quarter and one-half mile of a rail transit station in the Bay Area.

Evaluation of net energy impact of micromobility and access to public transit.
The net effect of micromobility on energy use is to be estimated, based on the analysis of individual trip data and repositions in the cities described above, as well as repositioning/recharging practices derived from interviews with service providers and managing contractors in Task 4, and findings on modal shift from the literature and Task 3 outcomes.

Task 3 Mode choice, induced demand, and infrastructure

Shared-micromobility Mode Choice Model

The research team produced a manuscript on the shared-micromobility mode choice model. The paper aims to understand and model people's mode choice decisions and preferences regarding shared micromobility vs other traditional modes (i.e., driving, transit, walking, biking, and taxis). Based on Washington D.C. travel survey data and shared micromobility trip data, a nested logit model was established with predictors of travel time, cost, access time, egress time and dew point temperature.

The team collaborated with the University of Florida on a paper manuscript titled "Shared Micromobility as a First- and Last-mile Transit Solution? Insights from a Novel Dataset", addressing the data gap that in empirical data regarding the integrated use of shared micromobility and public transit. As a result, much is unknown regarding the spatiotemporal patterns and characteristics of shared micromobility trips serving as first/last mile connection to transit. The paper leverages a novel dataset (i.e., the Spin post-ride survey dataset) that records thousands of transit-connecting shared e-scooter trips in Washington D.C., revealing spatiotemporal patterns of transit-connecting shared e-scooter trips in Washington D.C., resulting in some major policy insights regarding the integral use of shared e-scooters and public transit. The manuscript is under review by the Journal of Transport Geography

Privately-owned-micromobility Mode Choice Model

The team produced a manuscript focusing on private e-bikes mode choice model. This manuscript targets privately owned micromobility, more specifically, private e-bikes. By collaborating with OpenPATH, this manuscript utilized the trips data collected from Colorado e-bike incentive program to build a mode choice model that understands how private e-bikes replace other existing travel modes.

Analysis using the MEP metric revealed that in certain settings, e-bikes score competitively with private automobiles in terms of convenience of access to destinations (see Figure I.1.8.2). This work, completed in collaboration with the SMART Mobility MEP team resulted in a journal paper accepted into the Transportation Research Record.

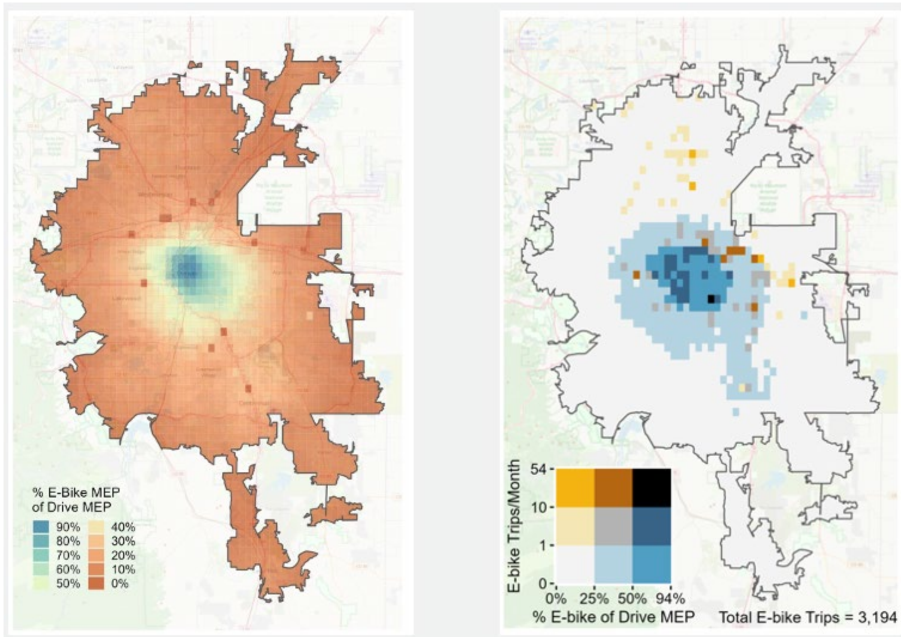

Figure I.1.8.2 MEP evaluation shows that e-bikes can replace the utility of private automobiles in some locations.

Task 4 Energy optimization of micromobility operations

The MITIE team continued engagement with stakeholders in municipal and industry settings, to explore opportunities for which improved energy optimization for shared micromobility systems may occur. Over the lifetime of a micromobility vehicle, the major energy inputs are 1) operational redistribution or rebalancing to meet demand for fleet operations, maintenance, or battery charging, and 2) manufacturing of the vehicle. Of these energy inputs, operational redistribution represents a much higher energy cost over the operational life of micromobility vehicles as compared to manufacturing energy costs. Therefore, scenarios focus on reducing operational energy input.

The team conducted a workshop for micromobility operations at the Shared Use Mobility Center Summit in Chicago in May 2023. The workshop focused on learning from participants and identifying pathways to optimize shared micromobility operations. Following the workshop, the team has collaborated with representatives from San Jose, California who participated in the workshop. The San Jose team is planning to use OpenPATH to collect data for evaluation of their micromobility programs. The team continues to identify collaborative opportunities for studies. In addition to the Colorado Energy Office's e-bike program, projects in Massachusetts and North Carolina have used OpenPATH for data collection.

Task 4A Characterization of "Alternative" Use and Emerging Forms of Personal and Freight Mobility

The ANL team completed a detailed manuscript comparing experimental results of two micromobility vehicles, an e-scooter and an e-bike. The study's main findings and experimental sections include:

- **Steady-state Experiments**: Operating both vehicles under non-accelerated conditions revealed that the e-bike had a considerably higher energy efficiency than the e-scooter.
- **Destination Runs**: Analysis of energy consumption during a hypothetical real-world trip—considering aspects like stops, turns, and elevation changes—again underscored the e-bike's superior efficiency.
- **Power Analysis**: A comparison of electric motor power versus human-provided power at varying e-bike assistance levels. This section also details the power distribution based on the state of charge.

- **Influence of Weight on E-bike**: A weight increase from 290 lbs to 350 lbs raised the energy consumption by 10%. Conversely, a decrease to 190 lbs resulted in a 1/3 reduction in energy consumption.
- **Coast Down Tests**: These tests exhibit a substantially higher rolling resistance for the e-scooter compared to the e-bike and help explain the differences in energy efficiency seen.
- **Charging Characteristics**: Both vehicles showcased charging efficiencies between 85.5% and 88.3%. Battery self-depletion showed a drop in state of charge of 60% over 72 hours for both vehicles.

Task 5 Micro-freight

Research to inform micro-freight scenarios

The team has provided refined micro-freight scenarios to the modeling teams for implementation in the Workflow. The timing of micro-freight and micromobility management operations scenarios for integration into Workflow are to be determined by Workflow managers, anticipated for runs as the modeling teams are able to fit them into schedules. As the MITIE project nears an end, the team continued to explore energy estimations of potential impact of cargo e-bikes. Recent efforts have included estimates for delivery use of the vehicles, as well as use of cargo e-bikes as "family vehicles", leveraging data collected from the Colorado Energy Office e-bike program.

Conclusions

The MITIE team made substantial progress during the past year. Having provided scenarios to Workflow teams, the MITIE team extended research into areas informed by initial findings, including exploration of the impacts of privately-owned micromobility. City- and state-level incentives programs are appearing across the U.S., encouraging accelerating adoption among private users. Through multiple analytical pathways, key findings suggest that micromobility, in both shared and private applications, result in energy savings, degrees to which vary by system and context. Micromobility is also found to improve equitability of mobility options, particularly for low-income and disadvantaged population groups, and among demographic groups that are revealed in the literature to be underrepresented among people who bicycle for transportation. Though FY 2023 is officially the last year of the MITIE project, collaboration continues, and opportunities persist in pursuit of exploration of the evolution of micromobility use and integration within the spectrum of mobility.

Key Publications

1. Akcicek, Cemal, Zack Aemmer, K. Shankari, and Andrew Duvall. 2023. Freewheeling: What Six Locations, 61,000 Trips, and 242,000 Miles in Colorado Reveal About How EBikes Improve Mobility Options. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-86388. https://www.nrel.gov/docs/fy23osti/86388.pdf.

2. Hoehne, C., Hanrahan, M., Shankari, K., & Garikapati, V. (2023). Mobility Energy Productivity and Equity: E-Bike Impacts for Low-Income Essential Workers in Denver. *Transportation Research Record*, *0*(0). https://doi.org/10.1177/03611981231193628

3. Sun, Bingrong, Venu Garikapati, Alana Wilson, Andrew Duvall. Estimating energy bounds for adoption of shared micromobility. Transportation Research Part D: Transport and Environment. Volume 100, 2021.103012. ISSN 1361-9209. https://doi.org/10.1016/j.trd.2021.103012. (https://www.sciencedirect.com/science/article/pii/S1361920921003102)

4. Shankari, K., Leidy Boyce, Ethan Hintz, and Andrew Duvall. 2021. *The CanBikeCO Mini Pilot: Preliminary Results and Lessons Learned*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-79657. https://www.nrel.gov/docs/fy21osti/79657.pdf.

5. Wilson, Alana, Andrew Duvall. A review of the literature on cargo bikes as a microfreight mode with a focus on the United States. World Symposium on Transportation and Land Use Research (WSTLUR) 2021. Conference paper. Presented August 9, 2021.

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NREL: Venu Garikapati, Bingrong Sun, Alana Wilson, Alejandro Henao, K. Shankari
LBNL: Tom Wenzel (Co-PI), Elliot Martin, Zach Needell, Michael Mills, Xuan Jiang
ANL: Michael Pamminger (Co-PI)
DOE: Jake Ward, Elise Keddie, Melissa Rossi, Raphael Isaac

I.1.9 Integrated Control of Vehicle Speeds and Traffic Signals for Reducing Congestion and Energy Use (Oak Ridge National Laboratory)

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Start Date: September 1, 2020 End Date: June 30, 2024
Project Funding: $3,150,000 DOE share: $3,150,000 Non-DOE share: $0

Project Introduction

In frequent stop-and-go driving, a significant amount of fuel is consumed due to unnecessary braking and subsequent accelerations. Depending on traffic conditions, over 25% of fuel consumption can be attributed to the considerable speed variations occurring in suburban and city driving [1]. Minimizing the amount of braking by anticipating what is ahead and decelerating gradually by coasting before arriving at the intersection can provide dramatic fuel savings and improve traffic flow. Congestion at intersections can be a significant source of such accelerations and decelerations, leading to unnecessary travel delays, increased energy consumption, and environmental pollution [2].

ORNL has developed signal control strategies that have shown reductions of up to 30% in network average travel delays when compared with those resulting from conventional pre-timed and actuated control methods [2]. Additionally, ORNL-developed predictive speed control algorithms that use existing SPaT data to optimize speed for minimized braking have shown potential for fuel consumption reductions of over 10% [3], [4]. However, these signal control and speed control strategies are not currently linked, which limits the possibility of optimal energy savings and traffic flow smoothing. By integrating the SPaT and speed control and employing connectivity to vehicles, it is expected that even greater efficiency and mobility benefits can be achieved.

In this project, we are developing and implementing fully integrated controls for traffic signal timing and vehicle speeds that will be evaluated with CAVs in a real-world demonstration to validate energy consumption and traffic flow benefits. The research employs advanced traffic simulations, CAV-in-the-loop dynamometer evaluations in ORNL's Connected and Automated Vehicle Environment (CAVE) Laboratory, and an on-road evaluation of a Toyota prototype CAV and eco-speed control system in the city of Chattanooga, Tennessee. The project will leverage an ORNL-developed Real-Time Mobility Communications and Control System (RyThMiCCS) to provide centralized data management and V2I communications [3], [5], enabling integration of the traffic signal and vehicle speed control, which have only been evaluated independently in previous studies.

Objectives

The overall project objective is to develop and demonstrate an integrated controls strategy that combines real-time traffic signal timing control and vehicle speed control in CAVs that results in efficiency gains of at least 15% and is validated under appropriate traffic conditions.

Regarding the prediction of CAV system performance based on microscopic traffic simulation, knowledge gained from this research will provide confidence in our ability to estimate the energy savings potential and mobility benefits for CAVs applications. These results will inform users of the limitations of the tools and highlight future needs for specific modeling methodologies that can improve such predictions.

The results of the assessment of the communication topology employed (direct point-to-point vs. cellular/cloud-based) are expected to provide insights to stakeholders regarding appropriate communication strategies that can/should be employed for specific CAVs applications.

Approach

The following is a description of the primary tasks of the project:

Task 1: Controls development and scenario evaluations via simulation: A detailed traffic microscopic simulation model of the test corridor will be employed for the development of the integrated signal timing and vehicle speed control strategies. Dynamic models for the integrated control strategy design will use V2V and V2I information of the traffic state to simultaneously determine optimal SPaT parameters and vehicle speed profiles that minimize energy consumption and traffic delays within the network. A range of scenarios will be evaluated to consider different technology options of interest.

Task 2: CAVE Laboratory vehicle dynamometer evaluations: Vehicle testing in the laboratory will be performed prior to on-road field evaluations using ORNL's new vehicle-in-the-loop dynamometer system. Traffic simulation data derived from Task 1 will be used to define the virtual environment, and real-time communications of simulated traffic signal data will be transmitted to a Toyota Prius Prime prototype CAV via RyThMiCCS. The developed algorithms will be operated with traffic simulation data to provide real-time data to the CAV, which will operate with direct speed control, while energy consumption measurements are made on the dynamometer of the actual vehicle operation.

Task 3: Field evaluation: The field evaluation will be conducted on the Shallowford Road corridor in Chattanooga. Speed controls will be directly implemented with signals in the corridor, with the aid of Chattanooga traffic engineers. The vehicle speed and traffic signal control systems will be tested under a range of traffic conditions, and the same scenarios considered in Task 1 will be evaluated during normal on-road operations. The Toyota prototype CAV will operate with direct speed control.

Results

The following sections describe key technical accomplishments and results obtained during FY 2023.

Energy Efficiency Validation using Chassis Dynamometer

The ORNL team has tested 18 sampled simulation drive cycles (with different penetration rates, speed control algorithms, and simulation entering time) on the dynamometer with the modified vehicle control model. Overall, the results are consistent between dynamometer testing and VISSIM simulation. More specifically: 1) dynamometer testing verified that the integrated control algorithm could significantly improve energy efficiency; 2) the relative energy saving (%) is consistent between the dynamometer testing and VISSIM simulation, which verifies that the VISSIM simulation can provide large scale and reliable evaluation results for energy efficient mobility research; 3) the energy

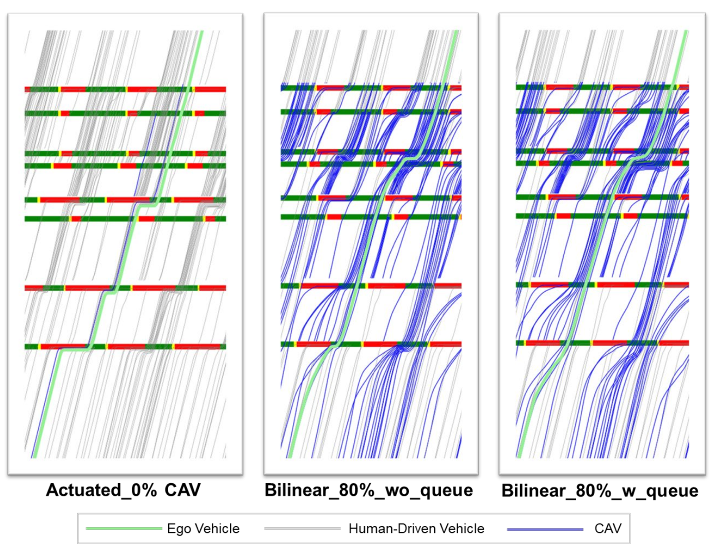

Figure I.1.9.1 The space-time diagram of the ego vehicle and the surrounding HDVs and CAVs (80% MPR).

evaluation results varies significantly by several factors: road geometrics, relative time to green/red, vehicle dynamics, and vehicle type (i.e., internal combustion engine vehicle, electric vehicle, hybrid vehicle).

Figure I.1.9.1 shows an example of simulated space-time diagrams of three selected ego vehicles that travel on the same route and enter the network at the same time. The surrounding vehicles are also plotted to illustrate the overall traffic condition. The left subfigure is from the baseline scenario where all vehicles are controlled by the default driving behavior model in VISSIM. The subfigure in the middle represents the integrated control scenario without queue length prediction, while the right subfigure presents the integrated control scenario with queue length prediction. This figure clearly shows that the integrated control algorithm can significantly increase the smoothness and reduce the number of stops for the ego vehicle. Moreover, integrating queue length prediction can further improve the trajectory.

Figure I.1.9.2 shows the actual battery powers versus vehicle speeds on the dynamometer testing for the same three selected comparison scenarios with Figure I.1.9.1. The changing pattern of the battery power aligns with the need to accelerate or decelerate the vehicle. Negative battery power occurs when it is regenerative braking. The figure shows that the energy savings for Scenarios 2 and 3 compared to the baseline scenario 1 are 26.3% and 26.9%, respectively. These energy benefits result from dyno testing are quite close to the simulation results in Task 1, where the simulated energy benefits for these two corresponding comparisons are 27.4% and 28.7%.

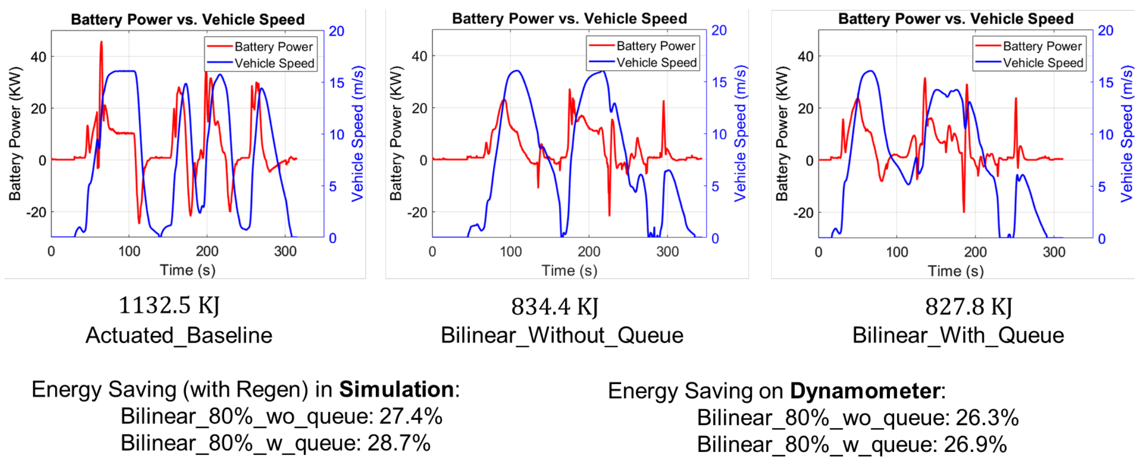

Figure I.1.9.2 Battery powers versus vehicle speeds for three matched comparison scenarios

Field Evaluation of Bilinear Signal Control Algorithm – Transportation System

Table I.1.9.1 summarizes the detailed experiments by each day in the test week. The bilinear signal control experiments were conducted from Tuesday, August 8, 2023, to Thursday, August 10, 2023. This section aims to validate the real-world performance improvements of the bilinear control algorithm over the baseline actuated control by comparing different performance measures along the corridor with the actuated control.

Table I.1.9.1 Detailed Field Tests

Date and Time	Participants	Note
August 7, 2023: 8:00 AM to 2:00 PM	**City of Chattanooga:** Ken Doyle, Tommy Trotter, Cindy Shell **Toyota:** Ben **ORNL:** Ross, Hong, Ali, Parth, Haowen, Max, Jinghui **NREL:** Tim, Andy, Qichao	Only vehicle control
August 8, 2023: 8:00 AM to 2:00 PM		Integrated signal and vehicle control (First day of school)
August 9, 2023: 8:00 AM to 2:00 PM		Integrated signal and vehicle control
August 10, 2023: 8:00 AM to 9:30 AM		Only signal control

For field experiments, practical constraints such as data coverage limitations and the availability of performance metrics necessitated a selection of the most feasible objective function. We have opted to prioritize the minimization of maximum occupancy as our primary goal. Occupancy, as defined within the GridSMART data system, quantifies the duration (in seconds per minute) a vehicle occupies a detector. Higher occupancy values indicate queue formation and potential traffic flow congestion. Given the constraints in data coverage, we used incoming detectors of minor streets and outgoing detectors of major streets to collect occupancy data. By selecting the minimization of maximum occupancy as our objective function in bilinear control, we aim to mitigate congestion and traffic flow interruptions. This strategic choice aligns with our practical considerations of available data sources and their relevance to our objectives during the field test.

Table I.1.9.2 presents a comparative intersection-level analysis of arrival on green, average speed, and throughputs at three experimental intersections, specifically examining two control methods: actuated control and bilinear control. The results indicate that, across all days, the average speeds achieved under bilinear control significantly surpass those achieved under actuated control (the same time of day and day of the week from the following week). On average, the improvement in speed amounts to a noteworthy 9.4%, and the average throughput under the bilinear control algorithm is 0.6% higher than that achieved with the actuated control. The overall enhancement in arrival on green amounts to a modest 1% improvement over actuated control. These results are indicative of the better performance of bilinear control when it comes to enhancing the mobility efficiency within the corridor. Further improvements should be made to the signal control algorithm to increase the system efficiency further.

Table I.1.9.2 Average Intersection Performance Comparison between Bilinear and Actuated (baseline) Signal Control

Experiment Date and Time	Arrival on Green (AOG)		Speed (mph)		Throughput (vehs/min)	
	Actuated (Baseline)	Bilinear Control	Actuated (Baseline)	Bilinear Control	Actuated (Baseline)	Bilinear Control
08/08 (Tue) 10:00-11:30	87.2%	90.0% (+3.2%)	14.6	15.6 (+6.8%)	157	158 (+0.6%)
08/09 (Wed) 10:00-11:30	87.9%	89.4% (+1.7%)	14.2	15.4 (+8.5%)	161	164 (+2.5%)
08/10 (Thur) 8:00-9:00	89.1%	86.9% (-2.4%)	16	17.9 (+11.9%)	150	148 (-0.13%)
Average	88.0%	88.8% (+1%)	15	16.3 (+9.4%)	156	157 (+0.6%)

Field Evaluation of Integrated Signal and Vehicle Control – Vehicle Evaluation

Figure I.1.9.3 presents different images recorded during the field experiment. The subfigure (a) shows the in-vehicle C-V2X and control devices. Subfigure (b) shows the 2017 Prius Prime Plug-in Hybrid vehicle, which operates in EV-only mode during the experiment. Subfigure (c) is a screenshot of the GridSMART camera at the Lifestyle Way intersection, which captured our test vehicle during the experiment. Subfigure (d) shows the front panel of the signal controller at the I-75 northbound intersection, which presents all the dynamic status of the controller. The subfigure (e) is captured from a drone video recorded during the experiment, which captured our test vehicle approaching the I-75 northbound intersection. Figure I.1.9.4 shows an example test scenario from the field experiment. The test vehicle was approaching the intersection of Napier Drive from the westbound direction. Multi-source data were gathered from the vehicle CAN bus, mapping PC, and signal controller. The green/red bars at the bottom of the figure represent the signal light status. The figure shows that the eco-driving controller is working as expected. However, the most important challenge for the field test evaluation is to identify the exact baseline comparison scenario for each controlled scenario. Ideally, the baseline case should be the same vehicle starting at the same signal light status (i.e., time to green/time to red) with very similar environmental traffic flow status. However, this requirement is almost impossible to achieve during an on-road experiment unless the experiment lasts long enough (e.g., six months) and can provide sufficient data to choose from.

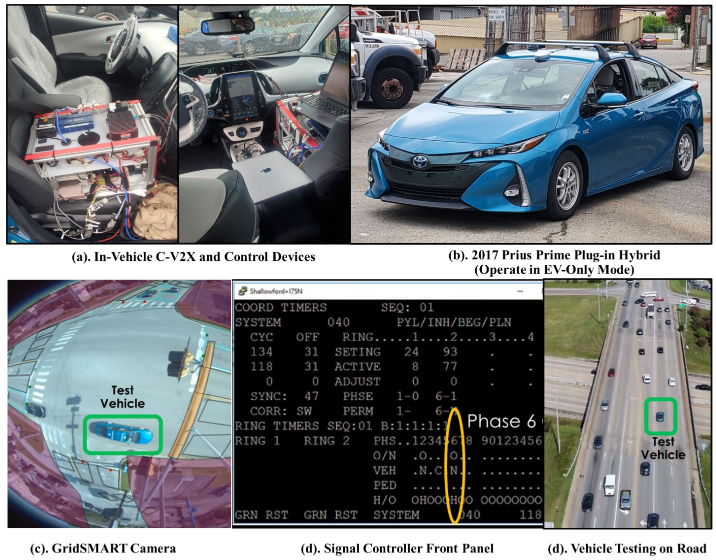

Figure I.1.9.3 Various images recorded during field experiments.

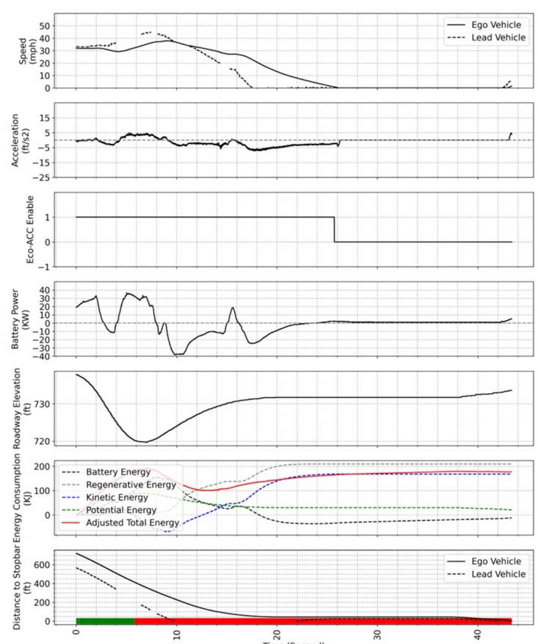

Figure I.1.9.4 An example of vehicle approaching the Napier Drive intersection from westbound direction.

During the on-road experiment, 75 intersection approaching scenarios were identified, including 36 scenarios with Eco-ACC enabled (14 actuated signal control and 22 bilinear signal control), and the remaining 39 scenarios are human-driven (19 actuated signal control and 20 bilinear signal control). In general, it's difficult to achieve statistically solid conclusions based on these scenarios. However, we think the results can at least shed some light on the potential benefit of the integrated control algorithm. To simplify the baseline identification requirement, we took the average energy consumption of all human-driven scenarios at the same intersection as the baseline of the Eco-ACC scenarios at this intersection. Figure I.1.9.5 shows the distribution of energy saving of Eco-ACC at each intersection approach based on the comparison between 36 Eco-ACC scenarios and the corresponding average baseline scenarios. The figure shows that there are positive energy savings at the majority of the intersection approaches (5/7). It is worth noting that the effect of signal control has not been distinguished in these comparisons due to the small sample size. Signal timing status is one of the most critical factors that will significantly affect the energy-saving results, as the arrive-on-green scenarios would very likely consume much less energy than the arrive-on-red scenario, disregarding the vehicle control status. In order to further clarify the energy-saving benefits of integrated signal and speed control algorithms, a significantly large number of experiments need to be collected, given the complicatedness of the integrated control mechanism.

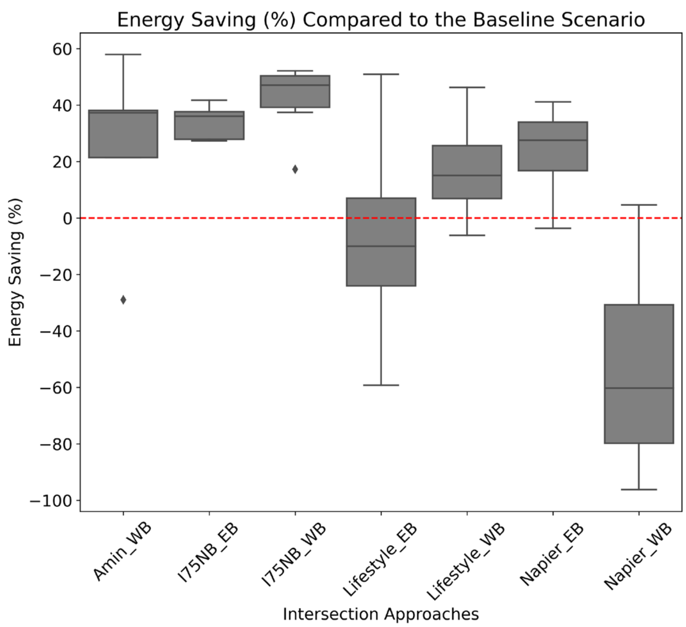

Figure I.1.9.5 Distribution of energy savings of Eco-ACC at each intersection approach.

Mobile App Development and Testing

A series of field experiments were developed to evaluate the communication latency and localization accuracy. Among the latency field experiments, we conducted two field tests in Knoxville, Tennessee, to measure the communication delay between the mobile app and the RyThMiCCS cloud communication system by driving a real-world vehicle in an urban environment. These tests were performed under a 4G mobile network with a download speed of 115-128 Mbps and upload speed of 19.3 Mbps using two Android smartphones, including a Samsung Galaxy S21 (advanced settings) and a Samsung Galaxy A21 (basic hardware). In addition, we conducted a localization test on the Shallowford Road corridor in Chattanooga, Tennessee, to quantify the accuracy of mobile-phone-based localization. As a result, the communication latency test demonstrated that the delay between the mobile app and the emulated signal controllers through the 4G cellular network is less than 1 second, which satisfies our design requirement for energy applications.

We conducted another series of field tests within the Shallowford Road traffic corridor in Chattanooga, Tennessee, to quantify the uncertainty in the vehicle localization process that relies on smartphone's GPS measurement. Based on the sampling of 1,284 points, we discovered that the raw mobile-sensed GPS coordinates have an accuracy ranging from 3.5 to 11 m, with a median of 5.2 m, as shown in Figure I.1.9.6. Because the GPS accuracy would affect the accuracy in the localization of the vehicle, we take advantage of the map-matching methods developed by previous studies to use the road network geometry received from online navigation application programing interfaces (APIs) to match and snap the smartphone GPS measurements to the vehicle's navigation route. This process can significantly reduce uncertainty in the GPS and vehicle speed measurement using smartphone sensors. Modern smartphones also provide enhanced geolocation capabilities, which adopt the combined features of Google location service, Android location service, and WiFi and Bluetooth scanning to improve the accuracy of the GPS measurement.

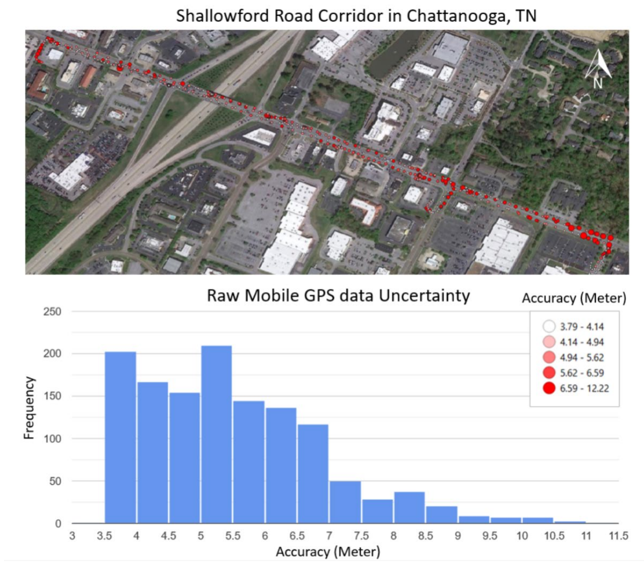

Figure I.1.9.6 Uncertainty analysis of the raw mobile GPS measurements within the field test in the Shallowford Road traffic corridor.

Conclusions

The ORNL team has made substantial progress in various testing (e.g., dynamometer testing, on-road experiment, localization accuracy, cloud communication latency) of the integrated vehicle speed and signal control algorithms. All of the planned milestones in FY 2023 have been satisfied. To summarize, the accomplishments are given in the following:

- Conducted CAVE lab testing and verified that the integrated control algorithm could significantly improve energy efficiency.
- Finished a one-week Chattanooga on-road testing of the integrated signal and vehicle control algorithms, where the ORNL team successfully demonstrated that the integrated signal timing and Eco-ACC vehicle control can be activated simultaneously and operated smoothly.
- Filed provisional patent application regarding the Oak-Ridge Eco-Driving Mobile platform, a Java-based mobile app for the speed control algorithm that can run on a cellphone.
- Produced four journal and conference publications, and two additional journal papers are under review.

Key Publications

1. Shi, Y., Wang, Z., LaClair, T.J., Wang, C., Shao, Y. and Yuan, J., 2023. A Novel Deep Reinforcement Learning Approach to Traffic Signal Control with Connected Vehicles. Applied Sciences, 13(4), p.2750.
2. Shi, Y., Wang, Z., LaClair, T.J., Wang, C. and Shao, Y., 2023. Real-time control of connected vehicles in signalized corridors using pseudospectral convex optimization. Optimal Control Applications and Methods.

3. Shi, Y., Wang, Z., Wang, C.R. and Shao, Y., 2023. Pseudospectral Convex Optimization for On-Ramp Merging Control of Connected Vehicles. Journal of the Franklin Institute.

4. Shi, Y., Wang, Z., LaClair, T.J., Wang, C.R. and Yuan, J., 2022, June. Real-Time On-Ramp Merging Control of Connected and Automated Vehicles using Pseudospectral Convex Optimization. In 2022 American Control Conference (ACC) (pp. 2000-2005). IEEE.

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NREL contributors include Tim LaClair, Andy Berres, Qichao Wang, Jibo Sanyals.

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I.1.10 Real-Sim: An XIL Platform for Mobility Technologies (Oak Ridge National Laboratory, Argonne National Laboratory)

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Start Date: October 1, 2020 End Date: December 31, 2023
Project Funding: $1,225,000 DOE share: $1,225,000 Non-DOE share: $0

Project Introduction

Rapid advancement in vehicle computing technology, connectivity, controls, and autonomous operation of advanced vehicles has increased the difficulty of testing, modeling and simulating vehicles and traffic control systems. Much of this difficultly stems from the complication of handling the new system of systems approach required to properly manage vehicles equipped with ADAS, CAVs, their surrounding environments, traffic networks, traffic control, and the various scenarios that greatly effect each one of these. Furthermore, traditional R&D tools, methods such as hardware-in-the-loop (HIL), and model-based design toolchains lack the capabilities necessary to address the complex nature of the environments in which the vehicles operate. As a result, through the "Virtual and Physical Proving Ground (VPPG) for Development and Validation of Future Mobility Technologies" EEMS core tools project, ORNL has begun to tackle many of these issues by making various portions of the combined systems swappable and enabled co-simulation with microsimulation and 3D virtual environment simulations to better tackle larger systems while still maintaining a true feedback loop, a feature inherent to advanced XIL methods.

Objectives

The Real-Sim platform will expand the capabilities of the VPPG Core-tools project feedback loop and add the capabilities of digital twins as well as greater real-world correlation by utilizing on-road/track data in a closed-loop process for validation of the performance of controls and simulated scenarios/environments. The Real-Sim platform builds upon XIL, simply defined as nearly any part of a system that can be "in the loop," either physically or virtually. This concept has become more evident as much of this transportation research has expanded beyond the vehicle into the traffic networks and traffic control devices. The Real-Sim platform broadens the capabilities of the VPPG and the portfolio of real, tangible hardware and software that researchers can immerse into simulated environments, while also adding on-track/on-road testing and digital twins to the feedback loop. The Real-Sim platform encompasses a wide variety of applications; Real controller – Simulated vehicle, Real vehicle – Simulated vehicle environment, Real SPaTs – Simulated traffic, Real time traffic – Simulated traffic flow results, etc. To maintain the experimental consistency, simulated environments (i.e., digital twins) become a key cornerstone, enabling realistic operation and reliable results within this approach. Moreover, this dependency on a realistic simulated environment is why the practice of making digital twins in simulation is a critical piece of the overall validation of most application-based projects. Figure I.1.10.1 illustrates how digital twins are used as the simulation environment for the various steps of the project as well as a feedback loop to determine how good a simulation is at replicating the real world. In particular, the digital twin provides an extremely similar development environment prior to any controls being deployed into the actual transportation system.

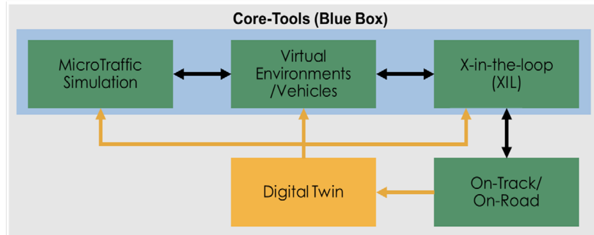


Figure I.1.10.1 Real-Sim concept

Approach

To fully realize validation through software, hardware, and vehicle testing in Real-Sim, the team will leverage its core capabilities in HIL to build upon pre-existing labs as well as build up one new unique facility through the support of the DOE. The Vehicle Systems Integration and Connected and Automated Vehicle Environment (seen in Figure I.1.10.2) labs are advanced powertrain and vehicle XIL laboratories that are focused on developing research and testing techniques to validate EEMS and SMART Mobility focused activities and projects. Particularly, the CAVE lab has the unique capability of being a steerable vehicle chassis dynamometer for testing fully automated vehicles with emulated, real sensor data streams to lidar, radar, and camera controllers as well as full sensor perception stacks. ORNL will collaborate with project partner ANL to leverage their signature automotive testing facilities and vehicle integration expertise to deliver connectivity and integration of existing laboratories to elevate XIL practices to an unprecedented level. By vetting the performance of this XIL process with existing data, this XIL environment will provide a resource for developing future transportation system control strategies that the consortium of national labs, industry and by extension DOE, will benefit from.

Figure I.1.10.2 ORNL CAVE Lab

Task 1: XIL and virtual environment 2.0, VPPG traffic microsim enhancements, and ANL mobile platform development

ORNL's Real-Sim platform leverages the ORNL VPPG to test the various transportation systems at the vehicle and/or traffic microsim perspective that are encompassed by EEMS/SMART Mobility. The first task in the construction of the Real-Sim platform will be to expand the XIL and virtual environment features of the VPPG. In addition, the traffic microsimulation capabilities (i.e., SUMO and Planung Transport Verkehr's [PTV] VISSIM) of the VPPG will be enhanced to include SPaT control, traffic control systems, and V2X systems. Finally, the ANL mobile testing and data collection platform will be constructed for feedback into the platform.

Subtask 1.1: Sensors - XIL and virtual environment 2.0. This task will expand the current XIL and virtual environment features of the VPPG. The focus of this expansion is developing the virtual environment sensor simulation (camera, LiDAR, global navigation satellite system [GNSS], V2X, etc.) as well as XIL interfaces between virtual sensors and their corresponding real controllers/hardware (also known as sensor emulation). This process will involve testing virtual environment sensor simulation models for quality and comparison to physical data. Furthermore, once a model with the appropriate fidelity is selected, the virtual data stream interface to the sensor controller hardware will need to be constructed to ensure the vehicle control algorithms receive data similarly to a real test condition.

Subtask 1.2: VPPG traffic microsim 2.0. This task enhances the traffic microsimulation capabilities of the VPPG to support XIL validation of three EEMS projects that ORNL leads or participates and for external users as released Real-Sim software product. These enhancements will include a flexible XIL platform capable of performing the complex "transportation as a system" co-simulation with various simulation toolchains and the capability to mimic the SPaT, V2X, and traffic control information from the traffic microsimulation into the 3D virtual environment (e.g., CARLA). Combined with the expansion from subtask 1.1, these tasks will construct the basis of the Real-Sim platform.

Subtask 1.3: Development of portable platform for V2X testing and data collection to enable XIL validation. Argonne will develop a portable experimental platform containing both infrastructure and vehicle-based components with the ability to coordinate and capture on-road experiments across varying roadway scenarios. The network of deployed infrastructure components will capture operation of infrastructure on actual roadways; provide control and communication on roadways where no traffic management controller exists and collect critical insight into traffic impacts based on specific research objectives. An additional vehicle-based component will supplement the infrastructure-based component to increase understanding of the environment surrounding the research vehicle. This transferable, vehicle-based platform will provide independent data collection from the vehicle-specific production sensors and installed sensors (video, GPS, acceleration, etc.), providing a full view of the vehicle and surrounding environment. The platform will integrate V2X communication capabilities built into both the infrastructure and vehicle components to transmit and capture signals broadcast as specific data collection or validation efforts require.

Task 2: Real-Sim platform and digital twins

The next phase of constructing the Real-Sim platform is creating a multi-layered digital twin of the intended transportation test environment. The multi-layered approach combines the digital twin creation techniques from traffic microsimulations and 3D virtual vehicle environments into a unified test environment for the transportation system. To elaborate, traffic microsimulation digital twins replicate the SPaT, traffic control, and infrastructure components at a transportation network level. On the other hand, virtual vehicle environment digital twins provide all the necessary 3D environmental fidelity for perception sensor feedback and mapping information to the vehicle to mimic the driving environment down to spatial positioning and geometry of the roadway. Creating a twin that cascades these two concepts together will enable the Real-Sim platform to operate within a high-fidelity digital twin that is similar to the over-the-road test environment, which is what allows simulation and XIL to correlate with real-world data since a common scenario and environment is required. A group of multi-layered digital twins will be created to support three current EEMS projects. A workflow will be established to create digital twins based on either sensor data of vehicles and/or infrastructure data, or open geographic information system (GIS) data if no other data sources are available. In the former case, the ANL vehicle will be used as the data collection platform. In the latter case, capability of Real-Twin project will be leveraged to help synthesize digital twins and reduce the needed manual labors.

Task 3: Validation of the Real-Sim platform using current on-road/track EEMS projects

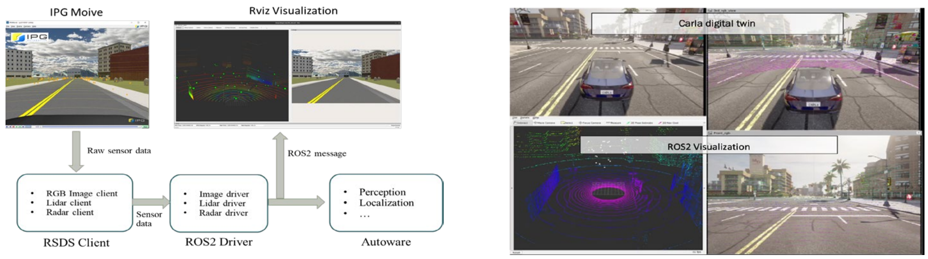
Utilizing data and test scenarios from current and past EEMS on-road/track projects, exercise the Real-Sim platform by using the VPPG (microsimulation, 3D virtual environment, and XIL) in the corresponding digital twin to replicate the real-world test scenarios. Replicating the test conditions of the data collected from on-vehicle testing and development will enable simulation and XIL to be directly correlated for verification to improve both the Real-Sim platform as well as the various individually simulated components such as sensors, control algorithms, traffic behavior, traffic infrastructure, and communication devices. This process validates the Real-Sim platform by correlating the output to EEMS/SMART projects using real-world data from onboard sensors, systems, and included physical hardware which will provide the enhanced fidelity necessary for vehicle and traffic network simulation to validate future control strategies and algorithms.

Results

Subtask 1.1: Sensors - XIL and virtual environment 2.0

The sensor integration work for FY 2023 has been completed (Figure I.1.10.3). As we migrating to Robotics Operating System 2 (ROS2) last year, we have built and test the pipeline of sending radar, RGB camera, and

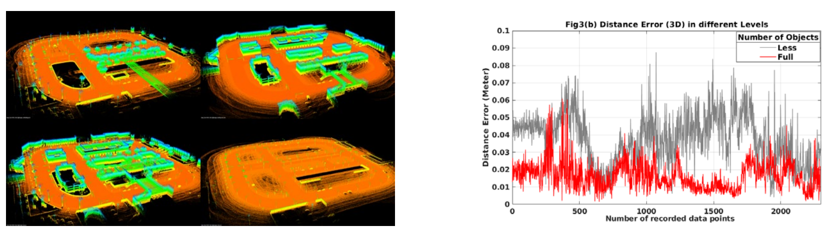
LiDAR data from virtual digital twin environment, e.g., IPG CarMaker and CARLA, to the ROS2 network. We will work on integration of the CARLA-Autoware with real vehicle controller and XIL simulation in the laboratories.



(a) (b)

Figure I.1.10.3 Sensor emulation from virtual digital twin to ROS2 network. a) IPG – ROS2. b) CARLA – ROS2

The other contribution is the study of how real is real for digital twin environment creation. By comparing the localization accuracy in different HD maps, we can find the optimal level of details that are needed for autonomous driving, thus saving the cost and labor effort for digital twin environment creation. Figure I.1.10.1 a) shows four levels of HD map from the same digital town, and Figure I.1.10.4 b) indicates the localization error comparison between the most detailed and the least detailed HD map.

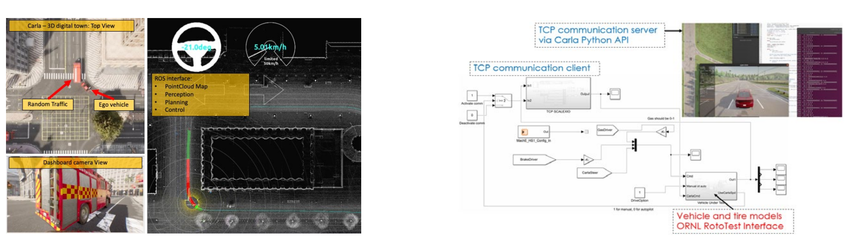


a) b)

Figure I.1.10.4 a) Point cloud map with different levels of details. b) Distance error between the most detailed and the least detailed HD map

Subtask 1.2: VPPG traffic microsim 2.0

The Real-Sim framework connects different simulation components and integrates various traffic and vehicle simulation tools, virtual environments, and XIL systems flexibly through a unique co-simulation interface called FIXS (Flexible Interface for X-in-the-loop Simulation, GitHub link: https://github.com/Real-Sim-XIL). The code has been refined and released on GitHub and available for public. We also tested the capability of CARLA-Autoware co-simulation successfully shown in Figure I.1.10.5. It demonstrates Autoware perception, planning and controlling the ego vehicle. Another work is incorporated CARLA simulator and ORNL's vehicle and tire dynamics models in Simulink to replace the existing CarMaker-based framework, shown in Figure I.1.10.5. XIL integration is undergoing in the CAVE Lab.



a) b)

Figure I.1.10.5 a) Demo of CARLA-Autoware co-simulation and b) integration of CAVE lab Simulink model and CARLA simulation

Subtask 1.3: Development of portable platform for V2X testing and data collection to enable XIL

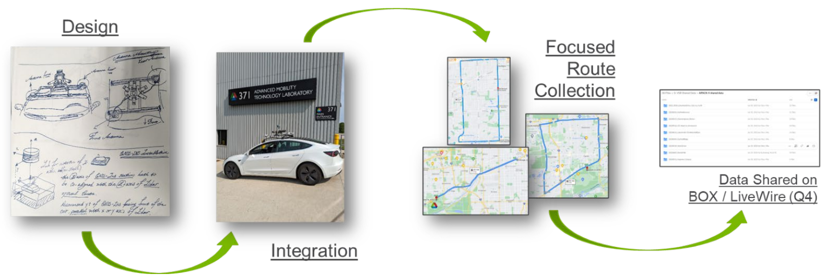


Figure I.1.10.6 Overview of FY 2023 progress in ALPACA

In FY 2023, ANL continued development efforts on two integral components of the mobile data acquisition system, known as the Argonne Labs Perception and Connectivity Activity (ALPACA) (see Figure I.1.10.6). These advancements were driven by the need to bolster capabilities and support research activities within the EEMS domain. The first key component, the Argonne Perception and Connectivity Kit-Vehicle (APACK-V), underwent a comprehensive refinement encompassing both hardware and software updates. Notably, the roof-mounted sensor array of the APACK-V is now equipped with the Novatel differential GNSS-INS navigation system, greatly improving localization accuracy. This upgraded system was meticulously calibrated and seamlessly integrated to enable data collection across a wide range of on-road activities, bolstered by its resilience to varying environmental conditions. The updated system achieved an accuracy of less than 0.5 meters, delivering a substantial boost to precision during subsequent data collection operations. In addition, the APACK-V received an enhancement through the implementation of a hardware-level signal-based synchronization. This synchronized all machine vision cameras through GPIO chords, instead of previous software-based synchronization strategy. significantly increasing the potential number of vision semantic frames that can be harmoniously integrated with lidar object detectors. This yields more stable 3D perception, providing clear advantages for all on-road data collection activities. Furthermore, the APACK-V adopted a different approach to CAN data collection, eliminating previous reliance on VSPY-X. To complement this updated strategy, a new time synchronization methodology was introduced. These technical refinements were complemented from a user-centric perspective, with the integration of a more streamlined GUI and driver system on the APACK-V. This user interface redesign aimed to reduce driver distractions and ensure a seamless and uninterrupted data collection process, whether dealing with raw or semantic data.

Efforts were directed towards improving the Argonne Perception and Connectivity Kit-Infrastructure (APACK-I) to enhance its experimental capabilities. These modifications encompassed the integration of a V2X API for encoding and decoding J2534 messages from dedicated short-

range communications (DSRC). Collaborative endeavors were also initiated with JTI, a portable traffic light manufacturer, to customize the traffic controller firmware, which included adding support for the NTCIP1202 protocol to facilitate a smoother integration with the Department of Transportation's CARMA Streets initiative. For the purposes of testing and validation, a simulated intersection was established just outside the Advanced Mobility Technology Laboratory. This simulated intersection served as a demonstrative platform for showcasing SPaT/MAP communication between APACK-I and APACK-V. Concurrently, comprehensive documentation has been created to provide clear and detailed instructions for setting up and effectively utilizing APACK-I.

Subtask 2: Real-Sim platform and digital twins

Development of multi-layer digital twin of the Shallowford Road Corridor, UTC FOA, and UA FOA have been completed as shown in Figure I.1.10.7. The workflow of digital twin creation has also been developed.

We have tested vehicle sensor emulation and perception with CARLA using these digital twins. We will compare the result with upcoming digital twin created using data captured in Task 1.3.

Figure I.1.10.7 Multi-layered digital twins for SMART2.0 Shallowford Road., UTC FOA MLK Boulevard., UA FOA McFarland Boulevard

In FY 2023, datasets were collected with the APACK-V across various geographic locations in the Chicagoland, encompassing Cook County, Du Page County, and Kane County. These datasets were acquired in diverse scenarios, including urban environments such as downtown Chicago, suburban areas, interstate highways, county roads, and rural countryside regions. The diverse nature of these locations ensures that the collected data comprehensively covers the spectrum of environments in which autonomous vehicles are expected to operate. The collected data has been archived and shared with project partners via the Box platform. Furthermore, we have taken a proactive step in promoting transparency and knowledge dissemination by submitting this dataset to the Livewire platform. The Livewire project is currently undergoing examination by DOE. Once this evaluation process is completed, the dataset will be made accessible to the public online in the near future, contributing to the advancement of autonomous vehicle research and development.

Subtask 3: Validation of the Real-Sim platform using current on-road/track EEMS projects

The Real-Sim has been integrated into EEMS096 SMART 2.0 integrated speed and signal control project and the UTC FOA eco-signal control project. The validation and XIL experiments for the other two projects are undergoing.

Conclusions

The foundation of the Real-Sim platform (Task 1) has been accomplished. Real-Sim interface has been released on GitHub for public. Significant amount of on-road data has been collected through the mobile data collection platform. Three Multi-layered digital twins have been development (Task 2) to provide a high-fidelity virtual environment to validate the Real-Sim methodologies. Sensor emulation, mobile data acquisition (DAQ) platform, and flexible interface have been updated from previous year which better support Real-Sim implementation in XIL co-simulation environment (Task 3). The major task in the last year of the project is to complete the integration of all the components of Real-Sim and test various CAV applications from current EEMS projects using Real-Sim. Correlation studies will be conducted to analyze data from road/track data and Real-Sim/CAVE lab to guide any platform modifications and calibrations with the focus of optimizing the correlation quality of the platform. The end goal is to provide an open-source Real-Sim Framework that can be easily applied to realistic scenarios for validation of advanced vehicle technologies and EEMS projects.

Key Publications

1. Shao, Yunli, Dean Deter, Adian Cook, Chieh (Ross) Wang, Bradley Thompson, and Nolan Perry. “Real-Sim Interface: Enabling Multi-resolution Simulation and X-in-the-Loop Development for Connected and Automated Vehicles.” SAE International Journal of Connected and Automated Vehicles 5, no. 4 (2022).

2. Shao, Yunli, Adian Cook, Nolan Perry, Dean Deter, and Chieh (Ross) Wang. "Real-Sim: A Multi-resolution X-in-the-loop Experimental Approach for Testing Connected and Automated Vehicles." In ACC22, pp. 3365-3365. IEEE, 2022.

3. Jianfei Chen, Haowen Xu and Yunli Shao. "Experimental evaluation of 3D digital twin fidelity requirements for autonomous driving research.", Presentation, 2023 American Control Conference (ACC23).

Acknowledgements

We would like to thank Alexis Zubrow, Jake Ward, and Erin Boyd as the DOE EEMS Program Manager and Technology Mangers, respectively and their continued support on this project.

I.1.11 Dynamic Curbs: A Data-driven Simulation Tool for Dynamic Curb Planning and Management (Pacific Northwest National Laboratory)

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Project Funding: $2,375,000 DOE share: $2,375,000 Non-DOE share: $0

Project Introduction

The rapid growth of new mobility services (e.g., ride-hailing, car-sharing, on-demand delivery, and micro-mobility) has dramatically increased demand for curbside parking and passenger/commercial loading zones in many U.S. cities [1]. This heightened demand for a finite resource necessitates the implementation of new and dynamic curb management capabilities to improve occupancy, throughput, and traffic disruption by parking search and space maneuvers.

Curbs are a critical interfacing layer between movement and arrival in urban areas---the layer at which people and goods transition from travel to arrival--representing a primary point of resistance when joining and leaving the transportation network in a core business district. Traditionally, curb spaces are statically supplied, priced, and zoned for specific usage (e.g., paid parking, commercial/passenger loading, or bus stops). But in response to the growing demand for curb space, some cities are starting to be more intentional about defining curb usage. A 2018 report by the International Transport Forum [2] presents an overview of curb management challenges that cities are faced with, as new mobility services and goods deliveries increase, and suggests that curb space should be flexible and dynamic to adapt to different uses and users.

A simple example of dynamic curb management seen in many cities is paid parking during off-peak hours and no parking during peak hours, to open an additional traffic lane. Recently, cities like Washington, D.C., San Francisco, and Seattle [3], [4], [5] have allocated curb spaces in heavy foot-traffic areas to passenger pick-up/drop-off zones during peak hours or have implemented dynamic pricing to incentivize driver behavior to reduce overall congestion. More dynamic use of curb space under extant field conditions---special events, disaster, and emergency management notwithstanding [6], could significantly decrease parking cruising time and double-parking, which would consequently reduce congestion, VMT, energy use, and GHG emissions.

As demand for curb access increases, transportation authorities have expressed a need for new methods to simulate various curb management policies. Due to the growing complexity of curb use by new mobility services, however, such actions are being taken on an ad-hoc basis. Currently cities measure curb performance using annotated street video, transit service GPS, and digital paid parking transaction data, where available. Yet cities often lack widespread A/B testing and the ability to reliably analyze the effects of curbside management policy decisions.

The project is a collaboration with the University of Washington's (UW's) Urban Freight Lab, Penn State University, LBNL's BEAM model development team, NREL's team from the SMART 1.0 curb metrics project, Lacuna, a smart cities technology company supporting the open-source Mobility Data Specification for municipal sensor platforms, and real-time curb occupancy data provider WiseMoving.

Objectives

This project's goal is to develop a city-scale dynamic curb use simulation tool and an open-source curb management platform that address these unmet needs. Simulation and management capabilities will include dynamically and concurrently number of spaces, allowed parking duration, time of reservation, and curb space use type (e.g., dynamic curb space rezoning based on supply and demand).

A microscale curb simulator will simulate activity of individual vehicles transferring goods and people at the curb at the city block-face level. The model will enhance LBNL's mesoscale (city-wide) travel activity model, BEAM, to simulate the impacts of various curbside uses and management strategies on overall traffic flow and travel demand as part of the VTO's Smart Mobility Workflow. We will use this BEAM enhancement to examine new methods for dynamically reallocating curb space throughout the day and will provide this capability to city and commercial partners through demonstration and pilot planning.

Approach

The project approach is broken into five, overarching tasks:

1. Curb (microscale) simulator implementation and integration with BEAM: Pacific Northwest National Laboratory (PNNL), UW, and Penn State are developing enhancements for PTV VISSIM, an off-the-shelf commercial transportation simulation software package, to simulate curb use and control under a broader array of use-cases and conditions by writing custom software linked to VISSIM's API. Then, for varying vehicle compositions, compliance rates, control regimes, and levels of demand, curb-use and adjacent traffic flow will be simulated. Traffic flow, as measured by novel, contextual fundamental diagrams are being integrated by LBNL within BEAM to measure city-wide travel impacts.

2. Curb allocation controller design: PNNL, UW, Penn State and Lacuna are collaborating on the development of the curb allocation controller via online, predictive optimization utilizing objectives (occupancy, VMT, emissions) and control variables (price, supply, maximum parking time) determined by stakeholder engagement. Additional task on developing optimal predictive control policies to automate variable message signs (VMS) at airports to reduce congestion and travel times at arrival and departure terminals.

3. Data collection, and microscale ground truth validation: UW, Penn State and Lacuna will provide existing curb management pilot data for the purpose of ground truth validation in collaboration with PNNL, Seattle Tacoma International airport and LBNL of both the stand-alone microscale simulation tool as well as BEAM outputs (i.e., comparing performance metrics in simulated and implemented scenarios vs. baseline).

4. Communications platform development: Lacuna will leverage experience in ongoing curb management pilots, and PNNL, Penn State and UW will extend a previously developed commercial loading zone communications application funded by VTO to integrate zoning control policies with a communications functionality for the purposes of technology demonstration.

5. Stakeholder engagement and technical demonstrations: Through the formation of stakeholder working groups (e.g., Seattle, Miami and Bellevue, Washington), the project team led by PNNL are demonstrating and receiving active feedback at relevant stages of technology development for evaluating curb management strategies, and the prospective analysis of alternative uses and measurement of rezoning tradeoffs. Taking advantage of the new teleworking norm, partner engagement will be virtualized; workshops and demonstrations will engage multiple related partners simultaneously.

Results

Impact of VMS on curb performance: We investigate the impacts of implementing VMS on curb performance at airports. By considering different driver compliance rates (DCRs), we aim to determine when the sign should be turned on and off to diverge traffic to avoid undesired externalities while enhancing curb performance. Using a validated agent-based microsimulation model, VISSIM, we analyzed the Seattle-Tacoma (SeaTac) Airport as a case study. We modeled sixteen VMS management scenarios and a baseline where the message sign is not displayed, diverging vehicles between the departures and arrivals access levels at four different moments (early morning, morning, afternoon, and late night). We quantified the effects of VMS using seven metrics, including curb productivity index, curb accessibility, queue length, queue duration, delay, vehicle counts, and emissions. The results of each scenario were compared against the baseline using absolute and relative changes and Repeated Measures ANOVA. Overall, VMS improved curb performance and traffic conditions at the airport, reducing emissions by 14.8% to 8.9%. Moreover, significant reductions in queue length (1,150 ft to 100 ft) and duration (15 to 144 minutes) were observed in the sending link under all VMS policies. In Figure I.1.11.1, we present the results of vehicle delay (VD), estimated between the vehicle diversion point and the beginning of the curbs for various scenarios. Here the first letter (E or F) denotes the VMS activation (E or Early for before queue starts in the sending link and L or Late for after the queue starts in the sending link), the second letter denotes VMS deactivation (E or L), the third letter denotes flow condition at receiving end (C or Congested and F or Free Flow), and fourth denotes the driver compliance rate (5% or 10%). VD varies depending on the congestion at the receiving link. If the receiving link was uncongested, deviating vehicles reduced the queue in the sending link without increasing the delay in the receiving link, reducing the total VD. Moreover, higher DCRs were associated with lower VD when the receiving link was uncongested. Deviating vehicles to a congested link led to two different outcomes. Firstly, suppose the queue in the sending link is significantly longer than in the receiving link. Deviating vehicles will not significantly decrease congestion at sending link and will exacerbate congestion at the receiving link, increasing VD. Secondly, suppose the congestion is similar in both links. Vehicles will not decrease their queuing time by diverging. Therefore, airports should activate VMS when the receiving link is uncongested. If the receiving link experiences congestion, VD can remain unchanged when the congestion is similar in both links or increase when the sending link is more congested than the receiving link.

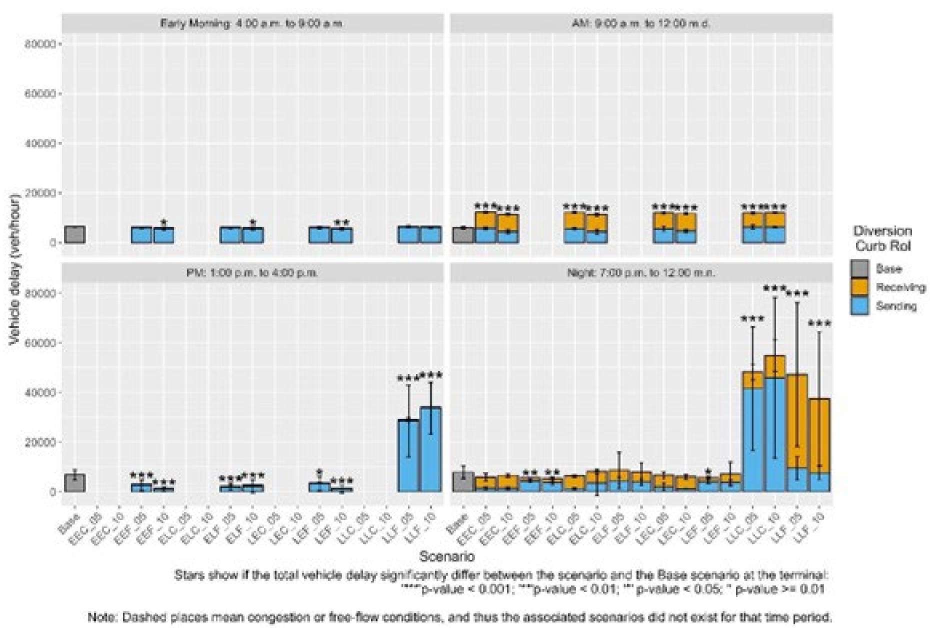

Figure I.1.11.1 Total delay across VMS scenarios and time periods at the terminal level

Microsimulation model validation: The SeaTac airport model was calibrated using data from August 5th, 2022, representing the year's busiest day. The model was calibrated at the Terminal approaches and Airport Expressway inbound, using a target Geoffrey E. Havers (GEH) of five, and obtaining an average GEH of 2.0 over the 24 hours. We compared the speed-flow data from August (the month which was used to calibrate the model) to the model outputs. The model outputs and the ground-truth flow distributions show the same trends (no significant difference at 95% confidence interval). However, for validation, we need to use ground-truth data different from the one used for calibration. For that purpose, speed and flow data from April and May were used. When comparing the model outputs with April-May data, we saw that flows are constantly higher in the model, and speeds (after 12 PM) are constantly lower. Since the model was calibrated for the busiest day of the year, those discrepancies are explainable. We adjusted ground-truth data by applying a factor to increase ground-truth speeds and decrease ground-truth flows as and compared the results to see if we can validate the model (Figure I.1.11.2). To evaluate the results, we applied three statistical tests: (a) Kolmogorov-Smirnov (KS) test (b) Wilcoxon–Mann–Whitney test (c) Anderson-Darling k-Sample test. We also plotted fundamental diagrams and applied Dynamic Time Wrap to do a time series analysis to compare the models to each other. Our null hypothesis for the three tests is that the VISSIM outputs and the adjusted ground-truth data distributions have the same distributions.. The results from statistical tests show that the model produces outputs that share a common distribution with the adjusted ground-truth data. also shows the differences between the model outputs and the adjusted ground-truth distributions.

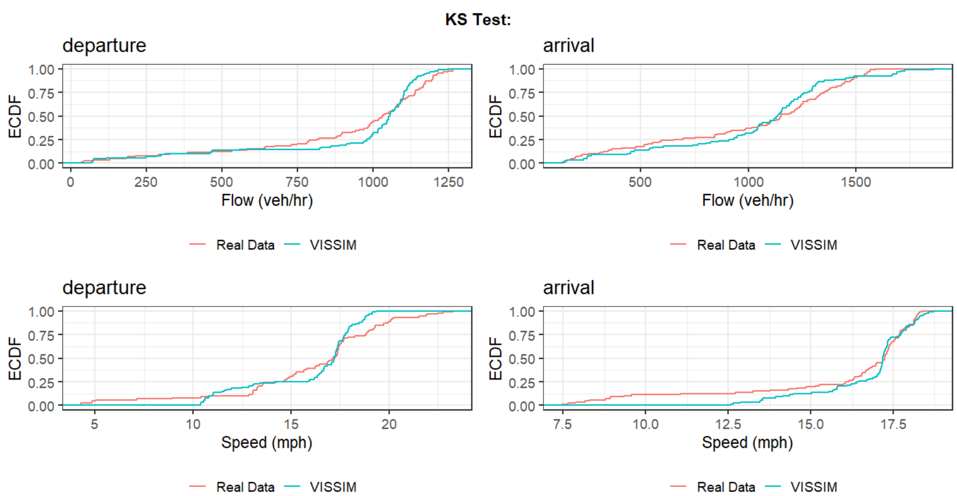

Figure I.1.11.2 Comparison between VISSIM outputs and adjusted ground-truth speed and flow distributions

Map-based web application: The architecture for processing real-time curb zone sensor data into available curb length consists of four main components: data sources, data processing, data storage, and data consumption. In this project, the primary data sources are the sensors that collect and report real-time information on the occupancy of curb zones through their gateways. The mobility data specification (MDS) sensor service fetches that sensor data from its respective APIs and processes it into meters of currently available curb length which could be used for loading activities. Both the raw occupancy and processed availability data are stored in a relational database (by the MDS collector service and curb data specification [CDS] curbs service respectively). Finally, the processed curb metrics are made available to the PNNL web app through an authenticated CDS curbs API. In WiseMoving's deployment, the sensors are installed at intervals along the curbs such that they will be able to observe the presence of a vehicle during a curb loading or parking event. They are capable of two-way radio frequency communication and use techniques such as detecting changes in magnetic induction to determine the presence of a vehicle in the curb zone. The sensors transmit curb occupancy data wirelessly to a central server via a network of distributed gateways. This data is transmitted in real-time and includes the sensor ID, reporting timestamp, and occupancy status of the curb zone. It is then processed by WiseMoving's servers to include information such as the last time occupancy changed. The curb availability data produced by this system is consumed by a map-based web application developed by PNNL. This app provides a visual map-based representation of the current and predicted available curb length data as shown in Figure I.1.11.3. It allows users to explore the curb availability data by location and even input their own vehicle length for a customized experience.

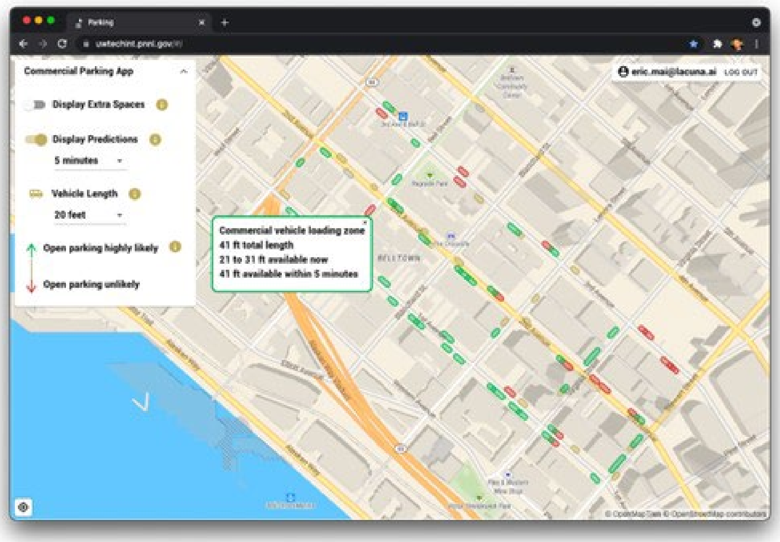

Figure I.1.11.3 PNNL's map-based web application

Conclusions

The project's third year has produced significant work on the topic of dynamic curb management with special focus on VMS deployment at airports. Various scenarios for VMS deployment were analyzed and different performance metrics were compared for each of these scenarios. We also validated the microsimulation VISSIM model of SeaTac airport with ground-truth data through various statistical tests showcasing the validity of developed microsimulation models. Finally, significant progress was made on developing the visual map-based web application that can display curb availability in real-time by investing data from curb occupancy sensors.

Key Publications

Accepted conference papers, presentations, journals:

1. Vasisht, et. al., "Estimating Driver Response Rates to Variable Message Signage at Seattle-Tacoma International Airport", Transport Finding Journal, September 2022.

2. Nazir, et. al., "Transit Fleet Electrification Barriers, Resolutions and Costs", Energy Findings Journal, September 2023.

3. Maxner, Thomas, et al. "Simulation-based analysis of different curb space type allocations on curb performance." Transportmetrica B: Transport Dynamics 11.1 (2023): 1384-1405.

4. Koch, James, et al. "Physics-informed machine learning of parameterized fundamental diagrams", In Proceedings of 102nd Transportation Research Board Annual Meeting, 2023.

5. Guitterez, J., Ranjbari, A., Nazir, N., "Evaluating the impacts of Variable Message Sign on Airport Curbside Performance Using Microsimulation", In Proceedings of 103rd Transportation Research Board Annual Meeting, 2024.

6. Nazir, et. al., "Mitigating Landside Congestion at Airports through Predictive Control of Diversionary Messages", SIAM conference on Optimization, 2023.

Key findings, press releases, and access to completed and future open-source software developed for this project can be found at https://www.pnnl.gov/projects/dynamic-curbs-urban-settings

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Key funded collaborators and institutions include:

1. Pennsylvania State University Larson Transportation Institute Lab: Dr. Andisheh Ranjbari (Assistant Professor), Mr. Jorge Guitterez (PhD student)

2. University of Washington Urban Freight Lab: Tom Maxner (PhD student)

3. Lawrence Berkeley National Laboratory: Dr. Zachary Needell, Mr. Tom Wenzel

4. WiseMoving (Errol Gayle, Reus Rosa)

5. National Renewable Energy Laboratory: Dr. Alejandro Henao

I.2 Core Simulation and Evaluation Tools

I.2.1 ANL Core Tools XIL: (Everything-in-the-Loop) (Argonne National Laboratory)

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Start Date: December 1, 2021 End Date: September 30, 2024
Project Funding: $1,200,000 DOE share: $1,200,000 Non-DOE share: $0

Project Introduction

With the rapid emergence and deployment of vehicle and communication technologies, CAVs have shown the potential to significantly improve overall transportation system efficiency, impacting travel patterns (demand, route choice), land use, network capacity and energy consumption. For highly automated vehicles, there are additional complexities compared to traditional vehicles due to multiple factors: on one hand the need for higher constraints on sensors accuracy, redundancy, and reliability, to ensure that information is combined correctly and remains valid under extreme scenarios and edge cases; on the other hand, the introduction of the cooperation aspect has shifted the focus of the analysis from the vehicle seen as a system to a network-centric approach. Due to the different nature and operational environment of CAVs, historical testing and validation tools and processes do not effectively capture their implication or reliably evaluate their effectiveness. Varying development and testing approaches need to be established to assess system impacts in terms of energy use, mobility, and environmental sustainability due to the introduction of these emerging technologies.

XIL experiments combine real hardware and virtual simulated systems with closed-loop interactions between them. As an extension to existing “component-in-the-loop” approaches previously developed by Argonne, XIL is tailored for connected and automated vehicles, where the type of real system is not necessarily fixed—e.g., a traffic light can be real or virtual. Demonstrated in EEMS Core 1.0 and SMART 2.0 project “Models and Workflows for Energy-Efficient CAVs”, the first iteration of Argonne’s XIL workflow combines hardware capabilities (chassis dynamometer, experimental CAVs) with one or multiple software tools, centered around Argonne’s RoadRunner. The framework provides standardized methods for integrating software and hardware components, file/model/result organization system, as well as user interfaces. As a result, the XIL workflow enables a seamless transition between the development stages, from the pure simulation environment to the experimentation on a chassis dynamometer, leveraging the core capabilities developed within the Vehicle-in-the-Loop task to quantify and improve the energy use impact of different CAV control strategies. As the role of XIL testing becomes more crucial in the characterization of advanced intelligent technologies, current capabilities must expand to integrate additional internal requirements and support the needs and efforts defined in conjunction with varying stakeholders.

The increasing penetration of smart cities across the globe is creating a highly connected infrastructure which is ideal for CAVs. As perception and communication technologies evolve and become available, vehicle manufacturers are starting to deploy vehicles with varying levels of automation and connectivity, driver-guidance functionalities, and various degrees of situational awareness. To continue in the mission of supporting VTO’s objective of quantifying CAV’s technology impacts, and ensure relevancy of the findings, the XIL vehicle research fleet should reflect the variety of current generation technologies commercially available, across vehicle classes, powertrain topologies and component technologies. In this effort, the current XIL fleet will be expanded and diversified to include state-of-the-art vehicles that provide suitable platforms to investigate cutting edge technologies and derive reliable vehicle models for energy use characterization.

To fully exploit the advancement in technology offered by the growth and diversification of the available research fleet, the XIL workflow capabilities will be refined and expanded to improve the efficiency and robustness of the testing in support of collaborative DOE EEMS research efforts. The improved XIL on-dynamometer workflow will enable the execution of a larger number of testing scenario due to the increased emulation capabilities (aero load, grade, lateral load, localization override), in a reduced amount of time with a higher degree of automation. One of the key advantages of the current XIL hardware-software shared architecture is its modularity which will be leveraged to increase the flexibility of the experimental setup and offers the possibility of decoupling and executing different components of the experiments on different platforms (computer or embedded controller running in real-time). The introduction of a standardized communication interface that governs the exchange of information between the research vehicle, the experimental facilities and hardware, and the virtual environment will provide the flexibility for evaluating custom CAV controls on different powertrain combinations available from the vehicle fleet and will streamline the workflow integration stage.

Bridging the gap between laboratory experimentation and real-world environments, the XIL framework will be extended to include testing and validation within a closed course environment (closed track, proving grounds) to characterize the performance of the vehicle within a controlled environment with foreseeable risks and flexible fidelities. This laboratory-to-road link will enable, and support, R&D efforts focused on gaining a deeper understanding of the impacts of the road, environmental and external conditions on CAVs operations, and evaluate the representativeness of virtual scenarios designed and tested in the earlier stages of the development process.

Objectives

This project focuses on the following main objectives:

- Enable new research vehicles for use in XIL experimentation to ensure that the XIL research fleet remains relevant with advancing automotive technologies.
- Expand the XIL workflow by improving the current process, expanding capabilities, and deploying developments to stakeholders.
- Evaluate VIL implementations outside of the ANL XIL toolchain for use in experimentation.
- Develop hardware and processes for transitioning on-dyno XIL experimentation to on-track and on-road testing experimental setups.
- Support synergetic activities between ANL XIL experimental and educational programs by acquiring hardware and developing testing equipment for testing in collaboration with Ecocar Universities.

Approach

During FY 2023 these objectives are accomplished adopting the following approach:

- Integrating two XIL research vehicles following a review of the current XIL fleet, and the greater US fleet. The two vehicles included a 2021 Hyundai Sonata Hybrid and a 2021 Toyota Rav 4 Prime.
- Expanding the XIL workflow with integration of methods for dynamic road load variation
- Improving the XIL workflow by developing and demonstrating a new real-time architecture with the ability to “split” the simulation and controls between real-time and non-real-time components

Results

Task 1: Integrating new XIL research vehicles

During FY 2023, Argonne Researchers integrated several new vehicle research platforms for use in the XIL testing environment. In prior efforts, a review of the current ANL XIL research fleet highlighted that while the vehicles available provide a strong mix of powertrain technologies with varying levels of automation, additional vehicles would be required to properly represent the U.S. fleet as it continues to advance and include newer automation technologies and more diverse drivetrains with a heavier focus on electrification. The vehicles selected for inclusion were an electrified light-duty pickup, the Ford F-150 Lightning, the 2021 Toyota RAV4 Prime, and the 2021 Hyundai Sonata Hybrid. At the start of FY 2023, two vehicles, the Sonata Hybrid and the RAV4 PRIME, were modified with communication overrides followed by dynamometer mapping to enable XIL integration. Following integration, the Sonata Hybrid was utilized within Task 2 supporting research efforts.

Continuing these efforts, Argonne researchers began the integration of two additional XIL research vehicles, a 2023 F150 Lightning and a 2023 Cadillac Lyriq. During FY 2023, the 2023 Ford F150 Lightning was acquired through rental following delays (1 year+) encountered through DOE/General Services Administration (GSA) procurement process. Following arrival, Argonne began instrumentation, data collection and decoding of vehicle communication data critical for XIL overrides. Further XIL integration of the F150 Lightning is set to take place in FY 2024. While the Lightning was a continuation of FY 2022 plans, the Cadillac LYRIQ was a new FY 2023 selection to provide an electrified platform on next generation GM architecture, and offer unique capabilities made possible through manufacturer support from Ecocar and SMART 2.0 collaborative efforts. During the third quarter (Q3) of FY 2023, the Argonne team reviewed methods of XIL integration for the Cadillac Lyric utilizing collaborations with GM to determine unique override methods available with GMs new high-security Global B architecture. A purchase for the Cadillac Lyriq was initiated in the fourth quarter (Q4) FY 2022 under Task 4 of this project, though due to delays in DOE/GSA procurement, the vehicle is not scheduled to arrive until the second quarter (Q2) FY 2024.

Task 2: XIL Workflow Dyno

Task 2A: Expanding the XIL workflow: Improving the Argonne XIL workflow and experimentation

2A.1 Improving the Argonne XIL workflow

In FY 2023, efforts have focused on further automation and enhancement of the ANL XIL workflow, with a specific emphasis on addressing the distributed architecture during various energy impact demonstrations. The demonstration of these improvements was a significant achievement and was primarily showcased during various testing campaigns, including the demonstration of “powertrain + speed” optimal control for the 2019 Chevrolet Blazer and “speed” optimal control for the 2021 Hyundai Sonata Hybrid HEV in a parallel project, SMART 2.0. Several automated processes developed for the previous experimental setup (the integration of virtual models and direct control into MABx) required modification to be seamlessly applied in the distributed architecture setup.

- An embedded code for the automated software setup during experiment preparation was tailored for the distributed architecture. This replacement, from a manual step to set up the software by running embedded code, not only saved preparation time but also reduced the potential for human errors.
- The automated signal recorder was improved, making it compatible with simulation specific (SimPC data), resulting in significant time savings by simplifying the merging of test results data from multiple sources after experiments.
- We designed and demonstrated a new monitoring and diagnosis model that operates within the simulation running in real time on a desktop (SimPC) for the new experimental setup. The prior monitoring model was limited to MABx.

- Some hardware-centric models integrating between simulation models and hardware sensing and execution were modified to be compatible with the distributed architecture.

These improvements were implemented and deployed in the full integrational testing campaigns for the energy impact demonstrations.

Along with the adoption of the distributed architecture experimental setup, the initial utilization of the direct override feature, for automated longitudinal control of the vehicle was deployed. This innovation enables "by-wire" control of the vehicle, effectively eliminating the need for a robotic driver. The elimination of the robot not only simplifies the process but also significantly reduces testing time by minimizing the preparation required for robot driver tuning. Notably, the direct override for Chevrolet Blazer was made possible through our collaboration with GM, exemplifying our strong partnerships.

Finally, another type of RoadRunner model was introduced for the first time, for tests with new architecture built by a flexible model-building process to verify its functionality in the experimental setup. This flexible model-building process in RoadRunner paves the way for expanding various hardware-in-the-loop tests, a focus that was previously limited to vehicle-in-the-loop tests. This innovative feature is set to undergo further improvements through automation and will be prominently demonstrated during the full integration test campaign for supporting another project, CDA, in FY 2024. This demonstrates our commitment to continuous improvement and expanding the horizons of our capabilities for the future.

2A.2 Expanding the Argonne XIL Workflow

To broaden ANL's XIL workflow on the dynamometer, we introduced the capability of dynamically varying aerodynamic load during a test into the workflow in real-time (Figure I.2.1.1). This aerodynamic load model was seamlessly integrated into RoadRunner, relying on empirical equations that model changes in aerodynamic drag, a foundation based on Michael Duoba's paper "Empirical Equations of Changes in Aerodynamic Drag Based on Direct On-Track Road Load Measurements for Multi-Vehicle Platoons" (SAE Technical Paper 2023-01-0830).

We further modified the RoadRunner models designed for the XIL workflow to facilitate the incorporation of changes in aerodynamic load onto the dynamometer. These changes were based on the gap between the real and virtual preceding vehicles. Two RoadRunner-generated car-following scenarios were rigorously tested with this configuration, featuring a maximum speed of 40 mph and an average gap of 30 m, all conducted with the 2019 Chevrolet Blazer (ICE).

However, it is essential to note that the full application of the change in aerodynamic load to the dynamometer, when translated to the grade, encountered limitations. The minimal change in the grade that could be applied on the dynamometer was found to be insufficient in accommodating the sophisticated impact of the aerodynamic load, particularly within the framework of the current test scenarios. This limitation underscores the need for further refinements to better account for the intricate dynamics of the aerodynamic load in our testing procedures. Future work on the dynamic aero load capability will focus on: 1) improvement of the chassis dynamometer grade signal resolution, to detect small amount of aerodynamic load variations, 2) investigation into alternate implementations to simulated aerodynamic load changes on the chassis dynamometer (dynamic variation of roadload coefficient "C") and 3) development of dedicated scenarios to investigate the impact of the aerodynamic load variations on vehicle performance.

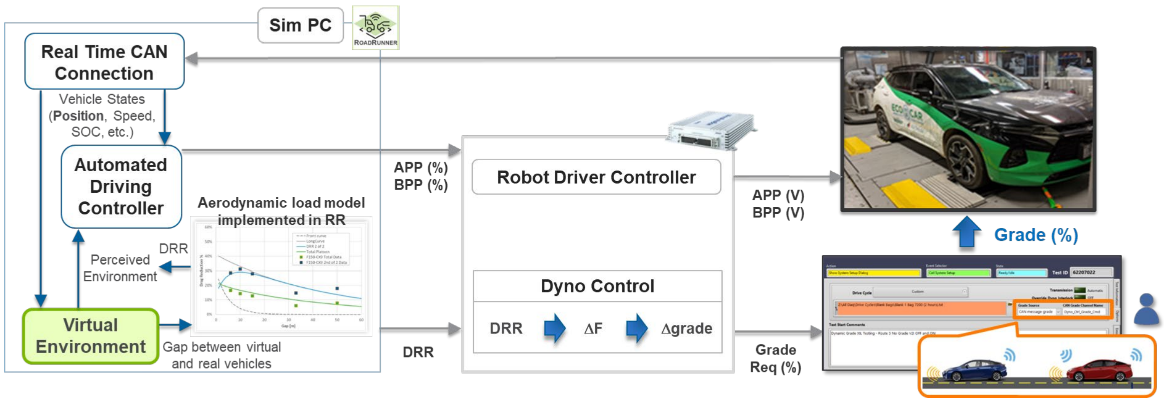

Figure I.2.1.1. Integration of aerodynamic load variations within XIL Workflow

Task 2B: Expanding the XIL workflow: Improving the Argonne XIL workflow and experimentation.

During FY 2023, Argonne researchers collaborated with DOT, Leidos, national labs, university, and industry partners to demonstrate the capabilities of U.S. DOT CARMA XIL/Virtual Open Innovation Collaboration Environment for Safety (VOICES) tools under the VOICES Pilot 2 program. VOICES Pilot 2 program is designed to demonstrate the VOICES proof of concept in which multiple geographically distributed participants coordinate through a synchronous testing environment and safe interoperability of different algorithms. To accomplish the Pilot 2 program, it was required to review newly developed systems (dockerized system, J2735 test and training enabling architecture [TENA] adapter, new network portal, etc.) literature and architecture, and attend meetings to discuss the technical process and system development for implementation.

Argonne researchers successfully set up VOICES adapters and established communication with the CARLA simulation platform essential for the first stage of VOICES Pilot 2 program (Event 0: Connectivity Check). These efforts consisted of developing a pathway to drive a simulated CARLA vehicle following predefined waypoints. ANL researchers continued to install the DOT tools (V2X-Hub, and TENA-SPaT-Plugin) and configured a scenario to integrate live traffic signal controller with CARLA simulation to support the final stage of VOICES Pilot 2 program (Event 2: Eco-Driving). This effort enables synchronizing live traffic systems controllers (TSCs) with simulated TSCs in the CARLA environment. In FY 2024, Argonne researchers will continue to determine the pathways to integrate VOICES tools with live traffic signal controller and vehicles on dynamometer. At the end of FY 2023, U.S. DOT software (CARMA XIL/VOICES) continues to be under development, and ANL plans to support the VOICES Pilot 2 program with hardware implementation of a vehicle on dyno in Q2 FY 2024.

Task 3: XIL Lab 2 Road

During FY 2023, ANL developed and documented a safety framework for on-road testing to provide a base architecture for future development and testing activities. This framework was designed for flexibility and customization depending on the specifics of each test system and application and includes a case study in applying the framework for university longitudinal control testing in the EcoCAR competition. The intent of this framework and associated documentation is to provide a foundational basis for each new on-road experiment, both within XIL and other efforts. While many industry organizations are developing automation and driver assistance features for production vehicles, these development activities and associated safety processes are very different from laboratories and universities conducting early-stage testing of prototype features on track and in public roadway environments. Due to this, it is necessary to develop and adjust a safety framework to guide research entities in safely enacting experiments with multiple vehicles and various degrees of connectivity/automation. The documented framework includes considerations for designing these prototype systems along with best practices for safely conducting experiments for longitudinal control. Future activities will include updating this framework to encompass lateral control feature testing in FY 2024.

Argonne teams also collaborated to define future-looking controller architectures capable of supporting on-road testing across XIL, CDA, EcoCAR, and other projects, while creating prototype mounting and driver interfaces to enable this testing. Argonne expanded HIL and bench setups with additional controller hardware identified in this process with the goal of increasing utilization of HIL/bench testing of diagnostics and other algorithms prior to deployment on road. Any road-based experiment presents an increase in challenge, complexity, and risk compared to a more controlled dynamometer environment. This challenge is particularly evident in experiments involving multiple test vehicles with active controls based on wireless communication, such as those in the CDA project. In FY 2024, the systems developed this year will be utilized to prepare for and execute on-road experiments spanning several projects.

Task 4: EcoCAR CAV Test Systems

During FY 2023, ANL has been working to prepare for the arrival and integration of the Cadillac LYRIQ to enable the vehicle to be used in XIL and EcoCAR test systems (as described in Task 1), along with acquiring and developing hardware systems to support EcoCAR testing and other on-road experiments. Through Task 4, Argonne worked with GSA to initiate the purchase of the Cadillac LYRIQ, though challenges with the GSA purchase process have caused significant delays in the original vehicle purchase timeline. The vehicle is now projected for delivery in March 2024.

Throughout this FY, ANL researchers worked directly with EcoCAR and General Motors to prepare for the integration of the Cadillac LYRIQ into both XIL and EcoCAR test systems. General Motors provided extensive data files and documentation in support of this process, including modifying onboard security of the vehicle and providing test harnesses to significantly reduce the complexity of integrating logging hardware for the LYRIQ. They also collaborated with Argonne to define a pathway for overriding the required longitudinal and lateral commands, capabilities that will be needed for XIL and EcoCAR efforts. Following continued delays in LYRIQ delivery, Argonne collaborated with an EcoCar university (Illinois Institute of Technology) to perform initial work a LYRIQ provided by the EcoCAR competition. Through this collaboration, Argonne was able to perform some early-stage testing of the Illinois Institute of Technology LYRIQ and capture valuable data from the vehicle. Argonne researchers were able to integrate the new GM harness connection on the Illinois Institute of Technology LYRIQ, collect data using logging hardware, and read CAN messaging in real time using a controller that will eventually perform XIL overrides for within both in XIL and EcoCAR efforts.

Lastly, ANL acquired traffic signal hardware and traffic controllers to be used for the deployment of a flexible connected corridor test system, where an automated lead vehicle will drive a scenario in front of each vehicle under test in conjunction with a sequence of synchronized connected traffic lights. This system may be deployable at any test track or closed stretch of road and can be flexibly configured to mimic a variety of connected corridor designs, layouts, and signal phase and timing setups. In FY 2024, the LYRIQ will be set up to act as this automated lead vehicle and an initial pilot of the multi-intersection connected corridor and lead vehicle test system will be developed at Argonne.

Conclusions

Through FY 2023, ANL's core capabilities for conducting XIL experimentation continued to advance with key developments in multiple areas including expanding XIL vehicle availability, improving the XIL software capabilities and workflow, and developing baseline processes and systems for XIL controlled roadway operation. These efforts will continue in FY 2024, with a focus on how XIL developments may be deployed within current and future EEMS, and VTO more broadly, efforts.

I.2.2 ANL Software Core Tools (Argonne National Laboratory)

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Project Funding: $1,975,000 DOE share: $1,975,000 Non-DOE share: $0

Project Introduction

Argonne National Laboratory excels at developing model-based systems engineering tools that accelerate the pace of innovation and research in the automotive and transportation sectors. The following software tools allow the VTO to achieve results with the same level of validity as OEMs when estimating the energy impact of technologies that support transportation decarbonization. In addition, these tools form workflows that are used to address stakeholder questions and advance technology evaluation and market introduction. They are essential for delivering critical insights to stakeholders; hence, they are part of the category aptly named: Core Tools.

AMBER is a model-based systems engineering (MBSE) platform from Argonne National Laboratory. Designed from the ground up as an extensible framework, AMBER allows engineers to create and customize workflows to fit their roles. This customization, in turn, gives each of them a streamlined workflow consisting of only the tools they need to answer their pertinent research questions. Software like Autonomie, POLARIS, SVTrip, RoadRunner, and others can be integrated into one common framework that leverages commonalities among their UIs and business logic, forming workflows that yield deep insights into the possible effects that artificial intelligence will have on energy and mobility. AMBER is the essential integration and deployment platform for MBSE.

Autonomie is DOE's preeminent vehicle simulation tool used to assess the energy consumption and cost of the powertrain technologies spanning DOE's entire research portfolio. Developed in collaboration with General Motors, Autonomie is a MATLAB©-based software environment and framework for automotive control-system design, simulation, and analysis. By having a plug-and-play model architecture and development environment, its application can cover energy consumption and performance analysis throughout the entire vehicle development process (e.g., model-in-the-loop [MIL], HIL, software-in-the-loop [SIL]). Autonomie has more than 300 licensed users including OEMs, suppliers, government entities, and universities in both the light-duty and medium- and heavy-duty automotive sectors. The Autonomie package contains a complete set of vehicle models for a wide range of classes, powertrain configurations, and component technologies including vehicle-level and component-level controls that were developed using dynamometer test data. Autonomie enables many types of studies including analyzing various component technologies, sizing powertrains components for different vehicle requirements, comparing the benefits of powertrain configurations, optimizing both heuristic and route-based vehicle energy control, and predicting transportation energy use when combined with traffic modeling tools such as POLARIS.

To better support DOE and its user community, several new features have been implemented in Autonomie. Some of the most significant accomplishments are described in this report. The concept of workflows is part of the design philosophy of Autonomie, and Autonomie has had great success in supporting user-defined workflows for a single vehicle. Under MBSE, many workflows exist: model verification and validation, design of failure modes analysis, vehicle validation and correlation, test data quality assurance, system-based HIL, system-based SIL, system-based MIL, large-scale study, and large-scale data analysis. Numerous OEMs and even other government entities have used these workflows and would benefit if they were supported in Autonomie. This project addressed these additional workflows by modifying the Autonomie framework to support customized workflows that do not directly involve loading a single vehicle and running a simulation. Before addressing these other workflows, compatibility with the current workflow must be maintained and demonstrated. This new framework is referred to as AMBER. Each release brings the software closer to the ultimate goal of providing a seamless process that enables use of Autonomie models and results with RoadRunner, Aimsun, and POLARIS (see Figure I.2.2.1).

Figure I.2.2.1 Model-based engineering scaling simulations from a single vehicle up to an entire city (source: Argonne National Laboratory)

Replicating the successes of Autonomie for ground-based vehicles, Aeronomie takes modeling to the skies with new models of drone aircraft for various classes of propulsion/powerplant architectures and application freight.

As the number of applications and workflows deployed with AMBER grows, the number of stakeholders also grows. To continue to deploy a reliable, industry-quality tool for OEMs requires following best practices, which include testing and issue tracking. In addition, OEMs require industry-grade licensing and deployment options. All of this, in turn, requires an information technology infrastructure of web servers, test servers, and even clusters to continue to keep the development on track and provide quality assurance.

To better support DOE and its user community, several new features and models have been deployed with AMBER. Some of the most significant accomplishments are described in this report.

Objectives

- Allow DOE's VTO to use tools like those used by OEMs to obtain consistent results related to state-of-the-art software for energy consumption, performance, cost, and mobility analysis.
- Democratize our tools and research by deploying the tools that we use internally to run our studies to the largest number of stakeholders possible and allow them to reproduce the results that appear in our published papers.
- Support a large user community (>300 organizations worldwide) including OEMs, the national laboratories, suppliers, and others by deploying workflows to them that accelerate their research.
- Deploy AMBER features that support multiple tools that live within AMBER such as Autonomie, Aeronomie, RoadRunner, and POLARIS.

- Develop new workflows that support the activities of the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium.
- Develop new models of electric VTOL (eVTOL) aircraft for urban air mobility in Aeronomie. These models can be used for energy consumption forecasting, component requirements, aircraft design, and flight optimization.
- Enhance existing Autonomie Graphical user interface and develop new ones for Autonomie and Autonomie AI.
- Develop and update training material and provide technical support to the 300+ organizations worldwide, which are critical to the successful deployment and adoption of the tools.
- Maintain and update the software development toolchain for the different codes for the 30+ third-party tools and maintain the HPC cluster and server infrastructure.

Approach

The approach is similar across all our software development practices. We use the Agile methodology and test-driven development to support our approach issuing new releases of the software. The Agile methodology allowed us to iterate quickly on the software, enabling us to issue new releases every night for internal use. JIRA is the tool we use to schedule fixes into public releases. Test-driven development enabled us to release a high-quality product every night for running unit tests in C# and for our nightly integration tests in MATLAB every night using the test software Jenkins.

For our Autonomie and Aeronomie model development efforts, we first perform a literature review to determine the state-of-the-art modeling practices. The Agile methodology is then applied to iterate quickly on the model, enabling us to issue new updates every night for internal use. Test-driven development enabled us to release a high-quality product every night.

Results

Four AMBER releases were deployed this year: 2023, 2023 Update 1, 2023 Beta (Aeronomie), 2024. These releases included the new applications: Aeronomie and Autonomie AI. The major development tasks of each of these releases are summarized below. Completion of each task resulted in deployment of a new feature in an AMBER release. Note that only the Beta Release has Aeronomie. This additional package makes the Beta release different from the others.

Released AMBER 2023

- Our OEM users have frequently requested synchronizing library changes across workflows. When a user updates their metadata library, they must close all currently open workflows in the user interface and then reopen them for AMBER to recognize the changes in their library. Having to manually resynch files by reloading workflows takes the user out of their developer-flow leading to more frustrating user experiences. To rectify this issue, file-watchers and a multithreaded backend have been implemented to both detect and resynch files across workflows as quickly as possible. This saves users from spending significant time reopening workflows and reloading vehicles, models, and calibration files.
- Another frequent request across all stakeholders is the ability to navigate and graphically modify a vehicle architecture (see Figure I.2.2.2). Vehicle architectures are often complex having several nested layers and hundreds of subsystems. Essential to understanding and modifying these MBSE architectures in the UI is being able to navigate this hierarchy efficiently with plenty of visual cues. Multiple workflows now integrate a navigable graphical view of the vehicle systems. That graphical

view also includes context sensitive parameter and file grids, which are filtered based on the currently selected system. The user can edit the vehicle files and parameters directly in those grids.

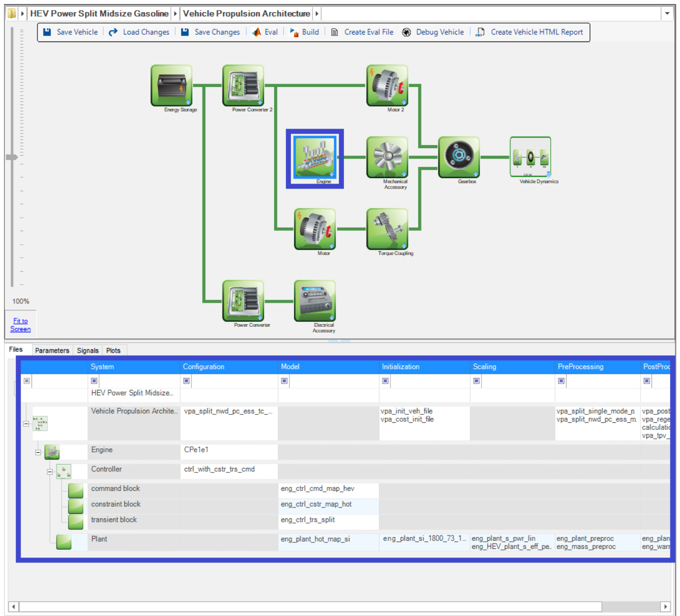

Figure I.2.2.2 Graphically navigating the powertrain, editing engine parameters

- Many of the coming heavy-duty studies require stitching together individual trips to form complete routes for trucks. These vehicles have parameters specific to their vocations such as power take-off or load which change over the different trips and need to be stitched together also. To deliver this functionality to both our internal users and OEM stakeholders, work commenced on a new Trip editor. The Trip editor was completed with the ability to concatenate cycles together, add new variables and to edit them graphically. That is, a user can edit their new vocational parameters and watch how the plots of those parameters change in response. The need for concatenating trips is illustrated in Figure I.2.2.3.

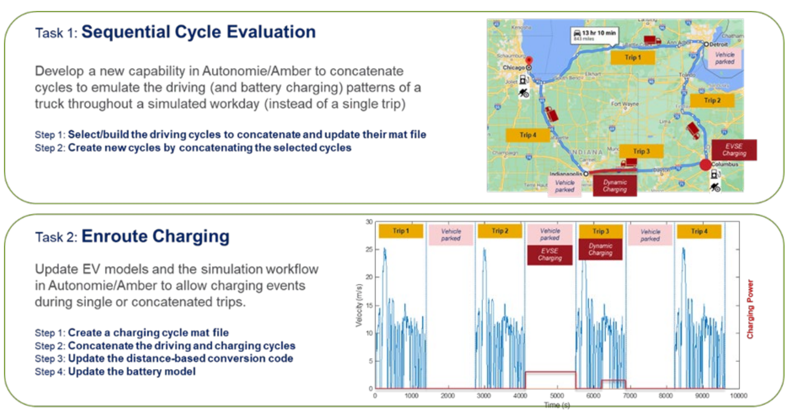

Figure I.2.2.3 Combining cycles to run heavy-duty and medium-duty studies

- Several sizing algorithms have been included in this release for both light-duty vehicles and Medium- and heavy-duty vehicles. A user can specify the vehicle performance characteristics such as 0 to 60 mph time, maximum climbable grade at a given speed, maximum speed, maximum towing, maximum all electric range, etc., and the algorithm will run simulations to determine the appropriate component powers and energy.

- Each library now contains its own variable dictionary, system and settings files. Only metadata for the variables used in that library are stored in its dictionary. This makes user libraries self-contained, shareable with others and can be completely source controlled. Information such as units, description, and data type is stored in these library specific dictionaries.

- New utility workflows were developed based on stakeholder requirements to help them maintain their library of metadata. The File Management workflow allows users to find references between files and between files and parameters. The Dictionary workflow provides for management of all the dictionary information, including type, description, map indices, no check parameters and other information users need to manage. Finally, the Compare Vehicles workflow helps users to quickly compare vehicles from a vehicle file as well as from simulation results.

- Running studies for DOE and DOT and other stakeholders requires multiple advanced features such as MPI, distributed computing, compilation, an expressive API, model library management, and model building. These 20+ years of features require constant maintenance and testing to continue running studies and reporting accurate results. The modeling infrastructure is vast and complex and always requires improvements as the type and requirements of our studies continue to evolve over the years. As always, numerous issues related to this framework were resolved including increasing the support size of Autonomie Lite cycles and vehicle property editing, among many others.

Released AMBER 2023 Update 1

- Several critical bug fixes were made to improve the Edit a Vehicle workflow when changing configurations. Changing configurations is a complex modification for it affects all child systems and files contained with-in it. This highlights the need to have more automated tests to be developed to reduce the burden on developers to do manual testing of features.

- The import a top-level configuration was refactored, and numerous issues were resolved. This feature is essential to provide users with a way to bring their own unique model architectures into AMBER.

- Additional API documentation was added, and the documentation was revised.

- A new Application was developed for internal stakeholders called the Development release. The release compliments the internal CI and Nightly releases. The UI is packaged with all licensed features; however, it functions without package extraction so that developers can choose which repos and branches to pull from.

- A new specific test procedure for battery electric vehicle (BEV) (short multi-cycle range and energy consumption test plus steady state, SMCT+), faster than the overall multi-cycle testing process, has been implemented as part of the Beta. The new BEV procedure has been validated against AMTL's test data. By utilizing this process, simulation time for BEV was reduced by 17%, and the difference in estimated energy consumption was very small (+/- 0.3%).

Released AMBER 2023 Beta

- A release of Aeronomie and AMBER was generated for the Beta. For all releases significant testing, and documentation were developed.

- A new Aeronomie Workflow was developed which allows users to visual their flight mission in 3D making it easier to understand what the mission profile is like. This makes it vastly easier for users to choose between different mission profiles. The new workflow can be seen in Figure I.2.2.4.

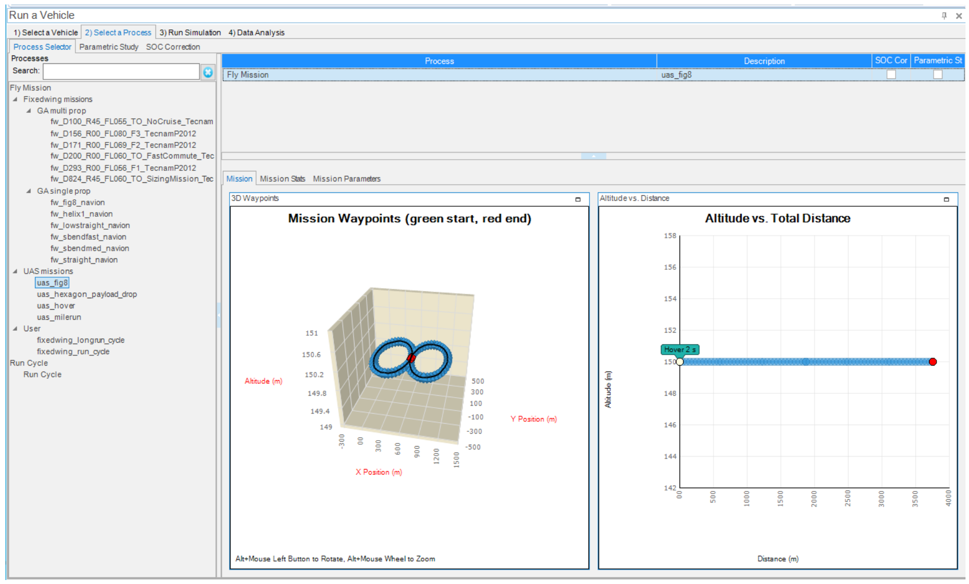

Figure I.2.2.4 Graphically Edit Trips with the New Workflow

Urban Air Mobility Aircraft Model Development in Aeronomie

The model of eVTOL aircraft in Aeronomie, like the Joby S4, has been upgraded to include longitudinal and lateral aerodynamic coefficients calculated using modified semi-empirical approach for Joby's unique design. We also developed a forward-flight capable Joby model capable of simulating a nominal 100-mile mission described by Uber air whitepaper. This capability helps us achieve the milestone of being able to simulate a straight-line mission using the two Joby models as can be seen in Figure I.2.2.5.

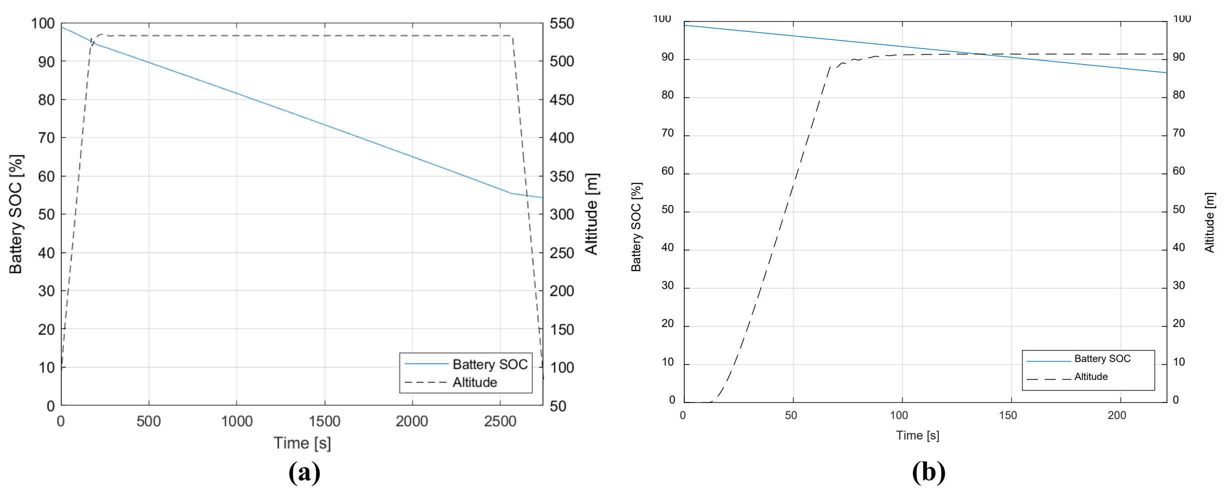

Figure I.2.2.5. (a) Battery state of charge vs. time and altitude for a 100-mile cruise. (b) Battery state of charge vs. time and altitude for a vertical climb and hover (source: Argonne National Laboratory)

Existing OpenVSP—a parametric geometry aircraft design tool—models were upgraded to accommodate change in propeller thrust direction and calculate the changes in lift and drag caused by this transition from vertical to horizontal flight. Further, VSPAERO is run to estimate the changes in coefficients of lift and drag (CL and CD) for propeller angles of 0, 30, 60, and 90 degrees, the flow visualization results for these can be seen in Figure I.2.2.6. In FY 2024, we will complete the eVTOL model by unifying the two flight models (forward and vertical) and modifying the current Aeronomie architecture to account for thrust vectoring. This will help us achieve a full transition model, which includes starting-up and climbing vertically, transitioning into forward flight, and then following a nominal mission.

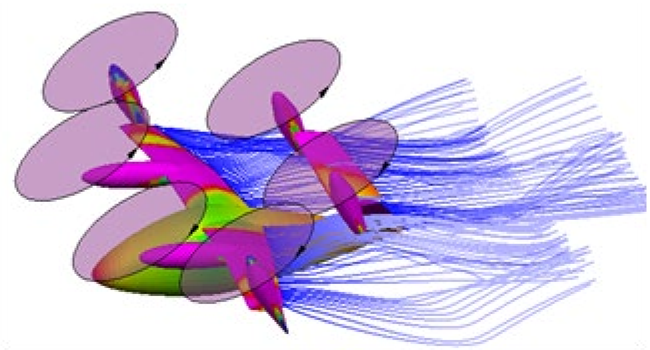

Figure I.2.2.6 Complex flow interaction visualized in VSPAERO during transition.

Released AMBER 2024

- An Autonomie AI workflow and application were developed and deployed as part of AMBER 2024. Autonomie AI provides 1,000 to 10,000 times faster prediction than Autonomie, which allows for adding accurate, validated energy consumption estimates to transportation modeling such as microsim tools or POLARIS. A user interface was developed that provides for the selection of vehicles and trips and then calls the Autonomie AI algorithm that was packaged as an encrypted .exe file with encrypted weights. A data analysis workflow was then developed to plot and analyze results. Figure I.2.2.7 shows the cycle selection of Autonomie AI.

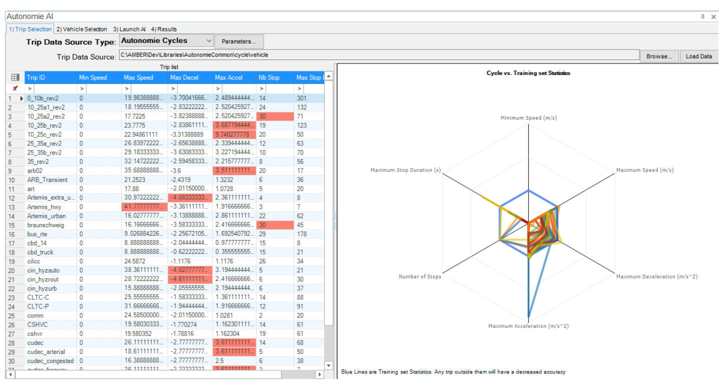

Figure I.2.2.7. Autonomie AI trip selection user interface

- SVTrip allows for the generation of trips stochastically from general route data such as the speed limit on roads. SVTrip bridges results from tools like POLARIS and microsim tools with applications such as Autonomie or RoadRunner. A user interface developed for SVTrip was added to AMBER 2024. This user interface allows for the selection of trip results produced from POLARIS or microsim tools, such as VISSIM or SUMO, and the generation of energy consumption results from such inputs.

- RouteGen is used to interact with online mapping applications such as HERE maps or Google maps to plot a potential route and pull information such as speed limits, grade, stops sign locations and stop light locations along a given route. A workflow was developed to interact with these APIs via a mapping control and generate a RoadRunner compatible route. The results of RouteGen can also be given to SVTrip to generate time-based cycles that are compatible with Autonomie.

- Multiple improvements to the graphical view were made to make it easier for users to visualize their powertrain architectures by adding the capture picture feature to the view. This is an often-requested feature from our stakeholders and is essential for the new transportation sectors which are being added to the AMBER ecosystem including aviation, rail, marine and off-road.
- Further support for these new transportation sectors is brought by the addition of namespaces to AMBER. Namespaces add the ability to have duplicated configurations when building a vehicle architecture. This feature can be used to add multiple locomotives to a diagram.
- The sizing process has been updated to offer the option of using compiled vehicles. This update allows for a 25% reduction in the time required to adjust vehicle sizes to meet the necessary performance criteria. However, compiling the model solely for these purposes delays the model building and compiling phases. Additional tests will be conducted before it is made available to the public users.

Technical Support

Answered more than 250 support questions related to licensing and usage of Autonomie from our user base.

Issues Fixes

We closed more than 280 issues related to AMBER and Autonomie this fiscal year.

Daily/Weekly Testing

Testing is a critical need. As code is modified and new workflows are integrated, the best way to verify that existing features work is to test them, and automated testing is the most efficient way to perform testing. Our MATLAB testing has been very successful in catching issues before the software is deployed to users.

Compiled vehicles are an integral part of Autonomie Lite and many of our internal studies. Ensuring that they are running properly is critical to continuing our work. Issues with the acceleration/sizing testing of the compiled vehicles were resolved. These tests are necessary to catch potential tunability issues with the compiled vehicles early. Currently, we do not have the computing capacity to run full tunability tests every night, so the compromise is to test only the tunability that would most directly affect the sizing of the vehicle. This strategy is not ideal, but it will catch some of the most critical issues early, when they are easier to identify and fix.

License Management & Packaging

We deployed AMBER/Autonomie 2023, AMBER/Autonomie 2023 Update 1, AMBER/Autonomie 2024 and AMBER/Aeronomie 2023 Update 1. The new Aeronomie application was part of the 2023 Beta deployment.

Autonomie AI is the tool used to support transportation simulation. This application is for users that are unfamiliar with vehicles and who want an easy way to run fleets of vehicles on cycles that they generate.

We have numerous software packages: Autonomie Energy, Autonomie MBSE, Autonomie Teaching, Autonomie Lite, Aeronomie, Roadrunner, and others. Each one of these softwares have their own user bases and will require updates on their own schedules as their respective user bases grow. To ensure that an Aeronomie update is not delayed on an Autonomie update, the model developers of each tool will have the ability to publish and deploy model updates for each tool independently of the overall AMBER version through the use of an AMBER package management tool.

Documentation and Training

The documentation was updated for the AMBER 2023 Release, the AMBER 2023 Update 1 Release, the AMBER 2023 Beta Release with Aeronomie and the AMBER 2024 Release. There were many improvements to document and over 500 pages of documentation. In addition, a separate documentation had to be written for

Aeronomie. Additionally, each application had to have its respective documentation updated for Autonomie Lite and Autonomie Express. Documentation is critical for user adoption. If users do not understand the software, they cannot use it to run studies. Over 8 new training videos were recorded and released this year.

IT Maintenance, Cluster, Servers, Website

To support our development and research we have three Hyper-V systems with over 40 servers and a 1768-node cluster that needs updates and constant performance tuning.

Downloadable Dynamometer Database

Argonne's Downloadable Dynamometer Database (D3) has provided a portal for data captured by Argonne's Advanced Mobility Technology Research team for over 10 years, supporting easy access to experimental data for DOE collaborators and public partners. During FY 2023, the Argonne team continued on a series of improvements to streamline the posting of data to D3. Based on a review of historical dataset structures, Argonne developed a revised data structure capable of maintaining high fidelity time series data and test metadata, while reducing file storage needs and continuing to work with historical and newly developed tools. The revised structure is a modified version of the National Instruments .tdms file, with a revised structure to contain metadata. Metadata includes both key test information (test name, type, comments, etc.) in addition to calculated data (SAE standard metrics, calculated energy use, etc.). Additionally, the structure was constructed to contain unique metadata related to charging or on-road operation, enabling similar loading tools to be used for these tests as well as those from AMTL dyno testing. Automated routines were developed, and all significant historical dynamometer testing datasets processed into this format for ease of test querying and comparative analysis. Additionally, in the last fiscal year, six new datasets from recent conventional and electrified vehicles were posted on D3 for public reference.

Conclusions

AMBER/Autonomie is the cornerstone of vehicle energy analysis at ANL and at DOE. The new features implemented in AMBER/Autonomie are focused on enabling DOE to continue to run large-scale studies with millions of simulation runs and to continue to support AMBER/Autonomie users who require the creation of detailed vehicles and tools to manage their vast libraries of models and calibration files.

These model-based systems engineering tools will accelerate the pace of innovation and research in the automotive and transportation sectors and will enable VTO to achieve results with the same level of validity as OEMs when estimating the energy impact of technologies that support transportation decarbonization. These tools provide workflows, which are designed with user feedback, to address stakeholder questions and advance technology evaluation and market introduction. These core tools are essential for delivering critical insights to stakeholders.

Acknowledgements

Sylvain Pagerit, Michael Juskiewicz, Paul Delaughter, Roulio Bellevue; Namdoo Kim, Ehsan Islam, Ayman Moawad, Daniela Nieto Prada, Bokai Xu; Nirmit Prabhakar, Francesco Salucci; Kevin Stutenberg

I.2.3 Livewire Data Sharing Platform (National Renewable Energy Laboratory, Pacific Northwest National Laboratory, Idaho National Laboratory)

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Start Date: October 1, 2021 End Date: September 30, 2024
Project Funding: $1,710,000 DOE share: $1,710,000 Non-DOE share: $0

Project Introduction

The Livewire Data Platform (Livewire) is a platform for securely sharing and discovering energy efficiency and mobility research data. It is a growing catalog of transportation mobility-related data and is maintained by experts at NREL, PNNL, and INL. Livewire can be viewed at livewire.energy.gov.

Livewire was funded by the VTO EEMS Program, and users include the EEMS research community and beyond. The platform leverages more than 30 years of experience from three national labs and provides a host of capabilities such as data preservation, data discovery, documentation, standard citations, metrics, security, and access permissions at no cost to users.

Objectives

Livewire is a hub for energy efficiency and mobility research data by providing state-of-the-art data management capabilities and services. By shifting the burden of data management to Livewire, the platform will enable DOE and other researchers to collaborate and share data around projects to reduce energy consumption, improve mobility access, and accelerate decarbonization of the transportation sector.

Approach

As Livewire's catalog and base of active users grow, the platform has evolved to meet and exceed needs to ensure secure data management and ease of use for users. Along with guidance from Livewire's Data Working Group, the Livewire team produced a whitepaper reviewing potential platform enhancements that was shared with the project's technology manager and used to outline potential areas of growth. Several of these ideas were implemented.

Results

Quarterly automated validation of users with access to Tier 3/restricted datasets was implemented. This process requires users with access to restricted datasets to verify ownership of the email associated with their access, ensuring that they still belong to the institution named on the nondisclosure agreement.

Thirteen categories for reference documents were defined, and all existing reference documents on Livewire were categorized (Figure I.2.3.1). Categorization of these documents assists users in locating useful datasets and supporting references and supports a significant user interface expansion for data stewards to manage references and publications associated with their projects on Livewire. A separate ability to collect publications and make them discoverable through a Livewire publications database was launched.

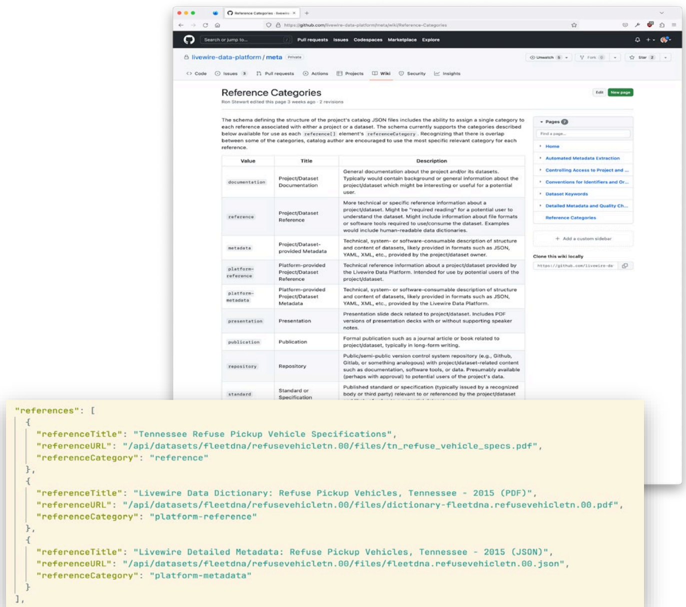

Figure I.2.3.1 Livewire reference categories were defined and existing reference documents categorized

The Livewire team has published detailed metadata and quality characterization for more than half of the datasets in Livewire's catalog. This useful information is an objective analysis of dataset completeness, statistical outliers, likely errors, and possible impact of likely errors. Detailed metadata also enables additional platform capabilities such as expanded search, introduced to help users locate datasets where their interests appear in table and column descriptions and data values (as opposed to a more basic search, which only scans a dataset's description), and the addition of dataset metrics, which assist in selection by showing potential dataset customers indications of dataset size (Figure I.2.3.2).

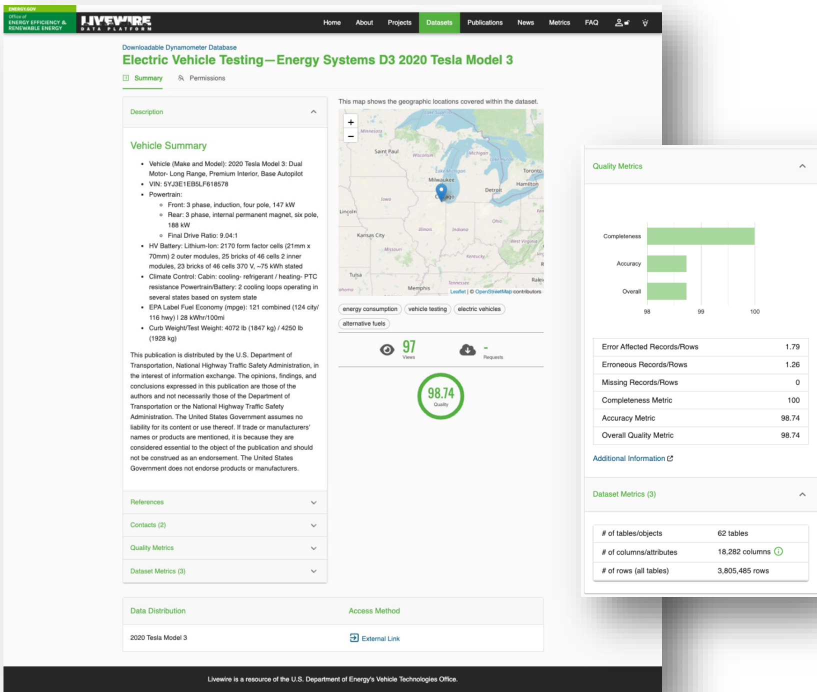

Figure I.2.3.2 Dataset metrics are displayed on the page to help potential users make informed decisions

With support from VTO, a quarterly Livewire newsletter was launched (Figure I.2.3.3). This publication shares timely information about new platform features and highlights featured data. Back editions of *Livewire News* can be found at https://livewire.energy.gov/news.

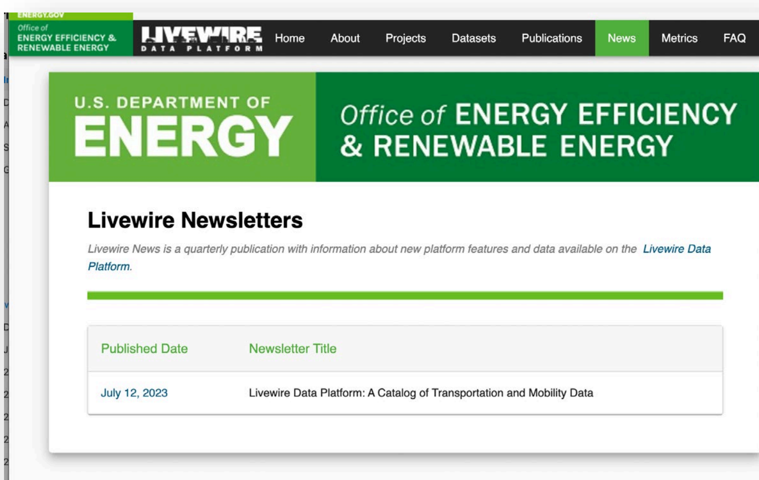

Figure I.2.3.3 The first edition of Livewire News was published on July 12, 2023

Finally, the Livewire team worked with partners at the Federal Highway Administration to support cross-federation of Livewire metadata to and from data.transportation.gov and similar catalogs. By sharing Livewire metadata in other catalogs, exposure of DOE's research projects, resulting data, and publications is broadened. This capability also enables additional opportunities for mobility research and collaboration across federal agencies.

Conclusions

The Livewire Data Platform team works closely with partners and uses state-of-the-art technologies to build a usable system for discovering, sharing, and preserving transportation and mobility data. Data and platform features are driven by user input to provide an efficient, user-friendly experience that enables researchers to find and share data to answer important transportation questions. By handling storage and management, empowering project leads to manage access to their data, and driving catalog growth, Livewire allows principal investigators to focus on their research.

Acknowledgements

The Livewire Data Platform team would like to thank the many researchers and project teams who provided input, feedback, and data to Livewire. We would also like to thank Pete Heywood, Jake Ward, and Melissa Rossi for their support.

I.2.4 Core Modeling & Decision Support Capabilities: FASTSim, RouteE, T3CO, and OpenPATH (National Renewable Energy Laboratory)

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Start Date: December 31, 2021 End Date: December 31, 2024
Project Funding: $1,200,000 DOE share: $1,200,000 Non-DOE share: $0

Project Introduction

This project is part of the program area to develop and improve core EEMS capabilities that enable research, development and deployment of advanced mobility solutions and enhance the EEMS Program's ability to address system-level transportation challenges. Advancements to the FASTSim, RouteE, Transportation Technology Total Cost of Ownership (T3CO) and Open Platform for Agile Trip Heuristics (OpenPATH) core capabilities under this project supports the overall EEMS Program goals to effectively evaluate energy and mobility impacts of future transportation technologies and services, and to identify the most promising pathways to reduce energy consumption, improve mobility access, and accelerate transportation sector decarbonization.

Objectives

Specific objectives under this project include ensuring that the supported capabilities are maintained/updated and made "turnkey" ready—such as through updating representation of the latest vehicles/technologies in the tools, and through improving software/interface robustness and tool automation. An additional objective is to improve EEMS topic representation in the tools—such as through embedding further CAV and enhanced powertrain/efficiency considerations in the vehicle modeling tools, and through advancing mobility data collection and incorporation of energy and environmental justice considerations through addition of OpenPATH to the EEMS core capability portfolio.

Approach

The project entails maintaining and enhancing the following four tools:

- **Future Automotive Systems Technology Simulator (FASTSim)** – a well validated and widely accepted vehicle powertrain modeling tool designed to capture the most important factors influencing vehicle fuel economy, performance, and cost. The modeling approach relieves users in many applications from having to work with high-fidelity input assumptions that add complexity, calibration, and computation burden without providing meaningfully improved accuracy. The base version of FASTSim uses generic component models to achieve good large-scale agreement with test data. Complexity can be added in customized FASTSim modeling to capture a wide range of real-world considerations and achieve even higher accuracy [1].

- **Route Energy Prediction Model (RouteE)** – a modular, energy optimal routing and navigation platform that allows users to co-optimize travel time and energy consumption for individual vehicles, fleets, or entire transportation networks. The core "RouteE-powertrain" component provides a mesoscopic energy prediction engine that considers real-time traffic conditions and road network link features to accurately anticipate energy consumption for a given vehicle when high frequency drive cycle data are unavailable [2]. RouteE models may be trained by running FASTSim over a large set of high-resolution real-world driving profiles, such as those hosted in the Transportation Secure Data Center (TSDC) or in the Fleet DNA database of commercial fleet vehicle operating data [3], [4].

- **Transportation Technology Total Cost of Ownership (T3CO)** – tool enabling levelized assessments of the full life cycle costs of commercial vehicles, considering the range of vehicle vocations and operational variations along with technology considerations associated with decarbonization. The T3CO methodology, vetted by industry and other stakeholders, employs best practices developed across DOE total cost of ownership (TCO) studies while addressing key gaps in standard methodologies [5]. T3CO leverages FASTSim to estimate the energy consumption of different vehicle designs when optimizing TCO under a given set of conditions.
- **Open Platform for Agile Trip Heuristics (OpenPATH)** – an open-source extensible platform for instrumenting human mobility—capturing details on travel behavior, modes, and associated energy use/carbon footprint. OpenPATH features continuous data collection and analysis via a smart phone app backed by a server and automated data processing. The tool empowers communities to collect and understand their own travel data while achieving place-based, locally relevant sustainable mobility goals [6].

Results

OpenPATH's focus on instrumenting human mobility differentiates it from the first three vehicle engineering models—FASTSim, RouteE, and T3CO. This, plus the fact that FASTSim is leveraged by RouteE and T3CO, motivated dividing the results discussion into two sub-sections, with the first highlighting results related to FASTSim, RouteE and T3CO, and the second sub-section focused on OpenPATH results.

Results Related to FASTSim, RouteE, and T3CO

Tool Enhancements

Over the past year of this core capabilities project work, many new features have been added to FASTSim to improve capabilities and enhance user experience. A semi-automated, web-scraping vehicle import tool has been developed and exercised to add 1,100 vehicles to the FASTSim vehicle database. Error messaging and logging have been improved to give users more informative error messages and more control over what events trigger errors. FASTSim has been released on PyPI so that it can be easily installed via "pip install fastsim" from any active Python environment, and since its release on May, this updated version of FASTSim has been downloaded nearly 1,700 times by Python users. Most of the Excel FASTSim features (e.g., vehicle import tool, function for calculating drag coefficient and rolling resistance from dynamometer coefficients, and window sticker fuel economy calculation) have been ported to Rust/Python FASTSim. A FASTSim command-line app has also been created so that non-Python tools can make use of FASTSim. This functionality has been used to connect the enhanced Rust/Python FASTSim with ADOPT. The FASTSim license has been changed to an Apache 2.0 open-source license, which has similar terms to the previous custom BSD 3-clause license but now allows standard license badging in GitHub, PyPI, and crates.io landing pages for FASTSim, while also protecting the FASTSim trademark. Lastly, efforts have begun to provide an enhanced documentation experience through FASTSim's GitHub page as an mdBook. Content will be added going forward, but this for now demonstrates the process in place for providing continuously updated, feature-rich documentation, including searchability, rendered equations, and graphics.

Key RouteE enhancements include a new version of RouteE-Compass that enables energy-aware, multi-objective routing at a national scale with modest compute resources. The new version of compass incorporates novel multi-feature edge weight calculations that are compatible with conventional path search algorithms and RouteE-Powertrain energy models. RouteE-Powertrain was updated to make models available with variable features sets (e.g., speed, road grade, turn angles) depending on what is available in a particular prediction application without the need to train new models. These enhancements have improved usability and versatility of the RouteE software suite.

RouteE-Powertrain and RouteE-Compass have both been released as open-source software on GitHub. Both codebases are documented in a common style that is shared with other NREL open-source tools such as FASTSim. Powertrain and Compass both have demonstration cases that rely only on publicly available data and models and require minimal expertise to interact with. In support of practical usability, NREL makes over 30 pre-trained conventional, hybrid, and battery electric RouteE-Powertrain models available for use with the open-source codebase. Similarly, RouteE-Compass examples that rely only on readily available Open Street Maps data are available. The open-source release is intended to encourage even more application of the RouteE suite across the spectrum of scale and technology readiness levels. Figure I.2.4.1 visually illustrates the resulting RouteE-Compass route options in the open-source demo case that relies only on Open Street Maps and pre-trained RouteE-Powertrain models.

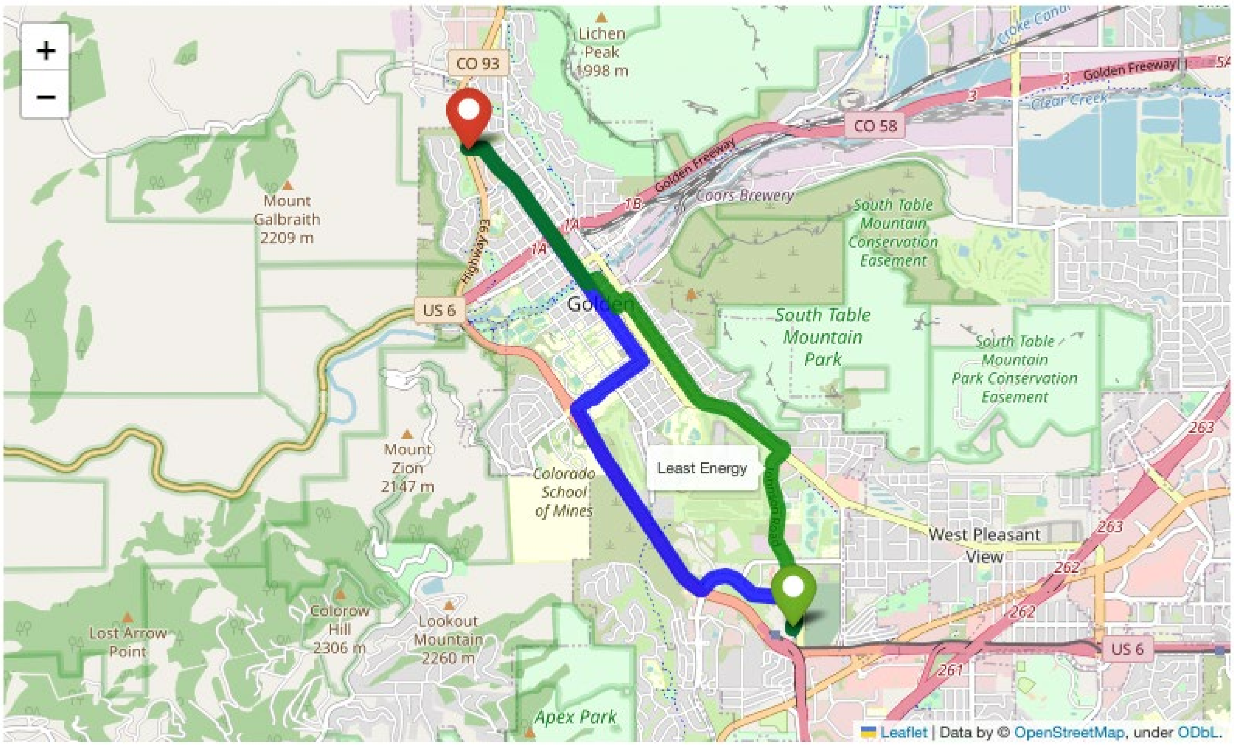

Figure I.2.4.1 A sample output from the RouteE-Compass open-source demonstration case showing the least time and least energy route options between an origin and destination in Golden, CO.

For T3CO, the team integrated FASTSim feature improvements to improve the user experience, including state-of-charge balancing, along with message and error logging. The team additionally streamlined inputs and outputs to enable use as a module within other analysis frameworks and streamlined constraint handling. This included adding constraints for speed trace miss to enable exploration of the PHEV design space from all-electric to all-fuel range capabilities. Building on the added optimization methods, the team implemented an ensemble capability to ensure robust results as illustrated in Figure I.2.4.2. The team also enhanced component calculations by updating maintenance and fueling dwell time costs, and added features for payload capacity costs, insurance, downtime, and resale. A new capability was added to output final optimized vehicle models as YAML files. This feature was then used to export eight commercial vehicle models in Classes 4-8 to the FASTSim public model library.

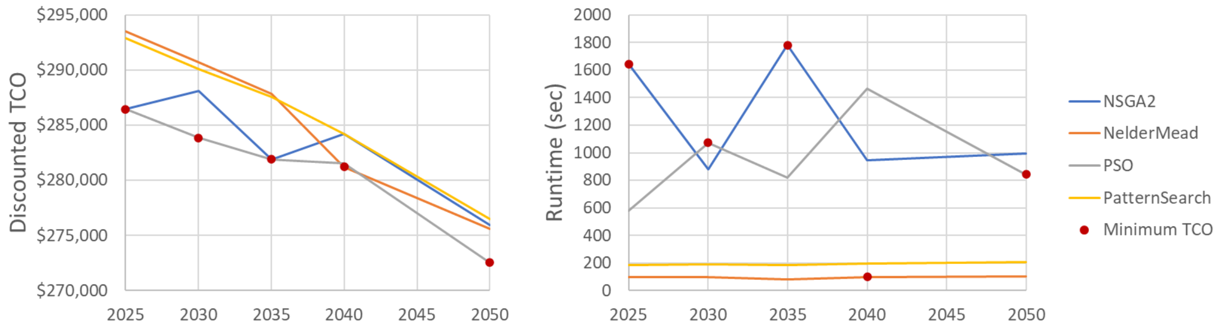

Figure I.2.4.2 T3CO ensemble optimization illustration for discounted TCO (left) and runtime (right)

Tool Applications

Consistent with the principle of being core capabilities, each of these tools and the enhancements enabled through this project are being leveraged to benefit applications under a variety of other projects. These include:

- Google Maps – In collaboration with NREL, Google Maps is leveraging FASTSim and RouteE capabilities to help people navigate to their destination quickly, while also optimizing for lower fuel consumption. As recently highlighted by Google's Chief Executive Officer, the fuel-efficient routing feature has so far helped prevent over 2.4 million metric tons of carbon emissions—the equivalent of removing about 500,000 combustion engine vehicles from the road for an entire year [7]. The feature launched in the U.S. in early FY 2022, and in FY 2023 NREL has supported continued expansion of the feature to countries in Europe, Africa, and Asia.

- Eco-Routing Potential in Heavy-Duty Fleets – In FY 2023, NREL worked with a major e-commerce company to explore the potential for fuel savings in their heavy-duty trucking fleet from eco-routing using RouteE-Compass. FASTSim and RouteE-Powertrain were both used to develop custom energy consumption models that represent the range of diesel truck configurations currently operating in the fleet. NREL found that even with strict business constraints (e.g., minimal tolerance for travel time increase), energy savings on the order of 1% were achievable with the multi-objective route optimization performed in RouteE-Compass.

- Transit Bus Electrification with Utah State University – In FY 2023, NREL developed a prototype interactive bus electrification dashboard around transit bus specific RouteE-Powertrain models. The dashboard relies only on publicly available General Transit Feed Specification (GTFS) data and provides insights to transit agencies on the potential for electrification of specific lines and an expectation of the resulting charging demands.

- Co-Optimization of Vehicles and Routes (CoVaR) – Under this project led by commercial vehicle manufacturer PACCAR, NREL is supporting deployment of RouteE models based on Class 8 linehaul on-road fuel consumption data, to inform more efficient fleet logistics and operations.

- Projects with Bosch, Eastman, Hyundai, Toyota, Ford, and EPA – These further external partner projects are leveraging FASTSim and/or T3CO. Note that work under SuperTruck III will leverage the new T3CO "sweep" functionality.

- SMART 2.0 BEAM CORE, Big Data Solutions for Mobility (BDSM), and Transportation Decarbonization Analysis (TDA) – All recent examples of projects funded by different programs within VTO that have variously leveraged FASTSim, RouteE, and T3CO. FY 2023 activities included leveraging T3CO-generated medium- and heavy-duty vehicles from TDA to train RouteE models for application as part of enhanced freight vehicle energy modeling for BEAM CORE. BDSM activities in the past year included adding stochastic energy consumption predictions into RouteE modeling to reduce model uncertainty when compared to a mean-value prediction method. The team is also leveraging on-road energy consumption data for multiple vehicles collected by ANL over repeated routes to further validate and improve the energy estimates.

Results Related to OpenPATH

Tool Enhancements

OpenPATH had three main accomplishments over the past year:

- Developing and deploying the admin dashboard. With this new functionality, initial versions of all OpenPATH platform components have been deployed. The admin dashboard supports scalability of the platform by allowing a *self-service* option for partners to download data on demand, without using valuable NREL researcher time.
- Significantly expanding the set of quantitative inputs supported by OpenPATH. The previous version of OpenPATH supported a static set of mode and purpose labels per trip. That static set is now the default, but partners can specify custom labels or even full questionnaires. OpenPATH also now supports qualitative inputs for places in addition to trips.
- Making significant progress on a complete rewrite of the phone application UI from Angular1 (currently at End of Life) to React. This involved developing a process to update the UI components incrementally, which lowered the risk of a major rewrite by spreading the changes out over multiple production releases. The team has also begun adding automated tests to the phone application as part of the rewrite.

Figure I.2.4.3 and Figure I.2.4.4 include app screenshots highlighting some of these enhancements.

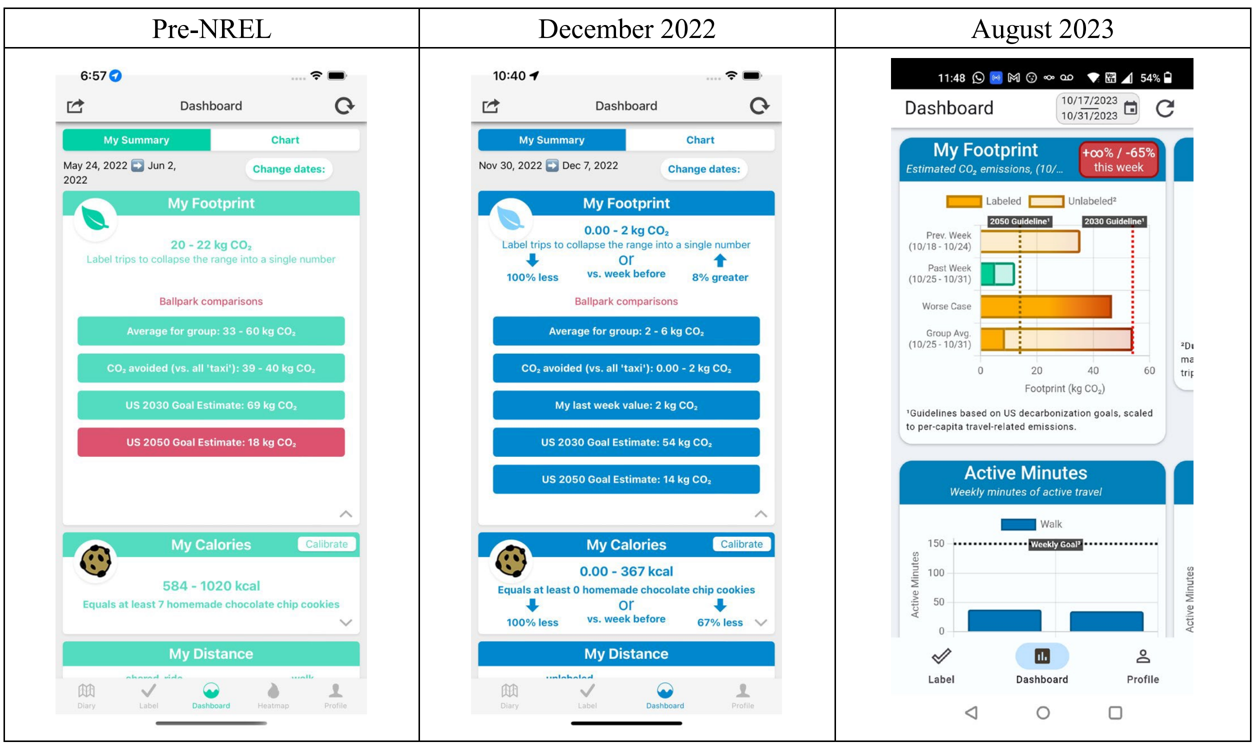

Figure I.2.4.3 Example of the app UI rewrite and associated usability improvements. This example focuses on the app dashboard.

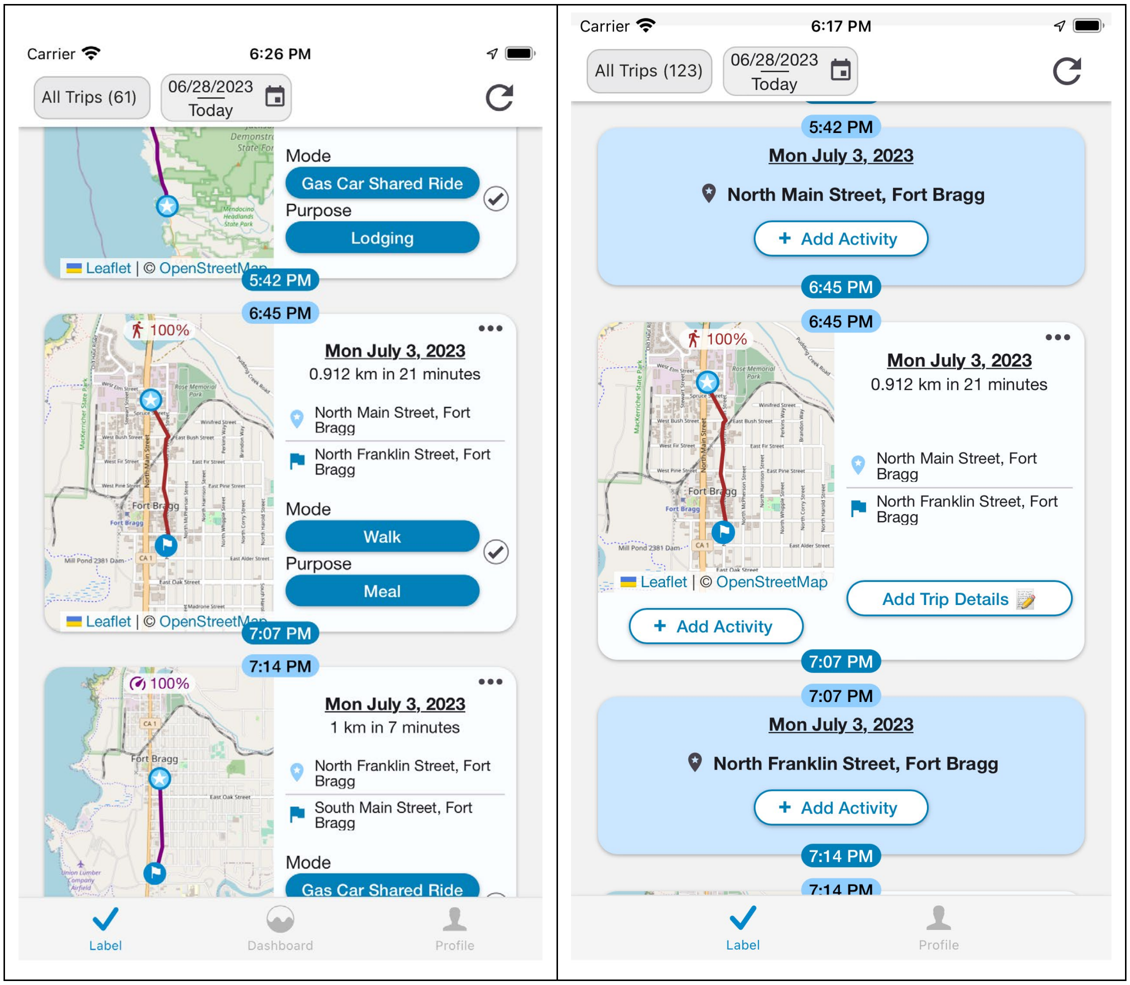

Figure I.2.4.4 Examples of the same travel diary with simple labels (left) and full time use surveys (right). This illustrates the configurability and extensibility of OpenPATH.

Tool Applications

The Colorado Energy Office has renewed its collaboration with the team by continuing to use OpenPATH for the next round of e-bike programs for low-income workers. The team has also begun exploring less intense data collection in partnership with the Denver Climate Action, Sustainability and Resiliency e-bike rebate program. Given the lower incentive in these programs, they have only requested labels intermittently through the longitudinal data collection period.

OpenPATH has also begun expanding beyond e-bike evaluation, with partners exploring incentives for commute mode shifts in Puerto Rico, Urban Under-Exploration in Kenya, and co-housing communities in California.

The team has also begun exploring integration of OpenPATH with other NREL tools. An exploration of integrating OpenPATH data with MEP calculations was accepted as a TRB Annual Meeting presentation and a Transportation Research Record journal article. Starting with a U.S. Agency for International Development partnership in Laos, the team is exploring use of OpenPATH to collect travel survey data that can inform EVI-X analyses in international contexts.

Conclusions

This project provides maintenance, updates, and enhancements for the core capabilities of FASTSim, RouteE, T3CO, and OpenPATH. These tools support numerous other activities funded by DOE and/or external partners. NREL additionally leverages this core capabilities project to ensure that these tools along with relevant data and research outputs are made externally accessible to further benefit other users and the broader research community. Future planned enhancements and applications of these tools include completing a full FASTSim code refactoring to include deeper object-oriented programming hierarchy and an order of magnitude even faster runtimes, fully updating the FASTSim vehicle database, publishing a validation report for RouteE, further leveraging both FASTSim and RouteE in collaboration with Google Maps to deploy eco-friendly routing across the globe, and making T3CO publicly accessible. Upcoming activities with OpenPATH include splitting energy and emissions calculations and using auto-updated grid mix numbers for the energy calculations to capture the joint impact of transportation electrification and grid decarbonization at a personal level. Overall, this project's tool maintenance and enhancement efforts together with the on-going and planned applications they support are helping to advance transportation efficiency, emissions reductions, and equitable mobility improvements.

Key Publications

1. Akcicek, Cemal, Aemmer, Zack, Shankari, K., and Duvall, Andrew. Freewheeling: What Six Locations, 61,000 Trips, and 242,000 Miles in Colorado Reveal About How E-Bikes Improve Mobility Options. United States: N. p., 2023. Web. doi:10.2172/1987488.

2. Allen, Michael, and Shankari, K. Count Every Trip: Finding the Uncertainty in Energy Estimates Made from Inferred Travel Modes. Innovations in Travel Analysis and Planning Conference. Indianapolis, Indiana, June 2023.

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I.2.5 Real-Twin (Oak Ridge National Laboratory)

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Project Funding: $872,000 DOE share: $872,000 Non-DOE share: $0

Project Introduction

Recent advancement in vehicle connectivity and automation technologies has increased the need for rapid testing and validating such technologies through modeling and simulation. The practice of modeling and simulation requires detailed design and implementation of scenarios, which often involves (1) developing a digital replication (scenery) of the system based on real-world data; (2) determining the vehicles and traffic systems (actors) to be tested in such environment; and (3) defining characteristics and behaviors (attributes) of the scenery and actors.

Within the research community, however, there lacks a unified approach to define and generate scenarios. First, scenarios generated for different technologies and objectives (e.g., congestion mitigation, energy-saving, decarbonization, safety) often have quite different areas of emphasis. For example, a realistic 3D virtual environment with high fidelity sensors emulation and vehicle dynamics and controls may be required for testing autonomous driving technologies for safety, but such level of fidelity in virtual environment and vehicle dynamics are often not required for validating traffic signal control optimization strategy, which instead needs realistic traffic signal controllers as well as detailed car-following and lane-changing behaviors for all vehicles in a traffic microsimulation. Second, even for the same technology and objective, scenarios generated by different research/industrial institutes, in terms of tools used, data collection and integration, and levels of fidelity for different components of the simulation, could be vastly different and cannot be easily transferred or validated by a separate facility. Third, the practice and process of generating and calibrating scenarios based on real-world data often involve significant numbers of manual steps that are time-consuming and prone to inconsistency and errors. Such a labor-intensive process also makes it difficult to scale up existing modeling and simulation practices for large-scale studies at the metropolitan and regional levels.

With the increasing demand for a holistic, system of systems approach for modeling and simulation, there is an urgent need for the research community to establish a unified approach to streamline the practice of defining, generating, and characterizing/quantifying scenarios for mobility research so that scenarios can be transferrable and recycled within and among different entities to advance mobility research in a consistent and scalable fashion.

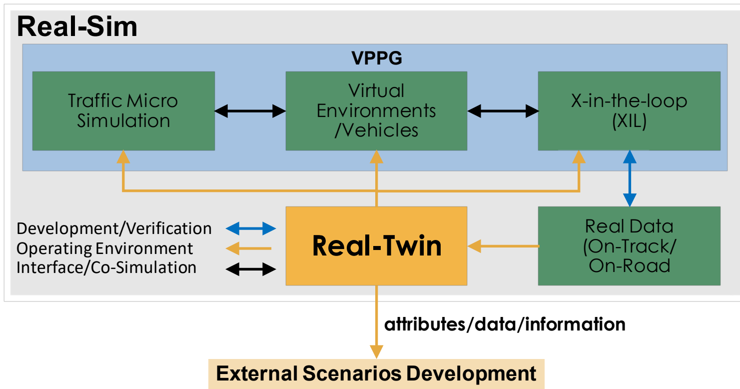

Figure I.2.5.1 Real-Twin: A new EEMS core capability for generating unified scenarios for advanced mobility research.

As depicted in Figure I.2.5.1, the Real-Twin project seeks to address these identified gaps by delivering a scenario generation capability that ingests real data and provides a twin for analyzing decarbonization opportunities and evaluating mobility objectives in simulation, virtual environments, and/or XIL.

Objectives

The overarching goal of Real-Twin is to deliver a realistic and consistent scenario generation capability that ingests real data and provides a twin for analyzing decarbonization opportunities and evaluating mobility objectives in simulation, virtual environments, and/or XIL. A typical Real-Twin usage would be as the following: users select the technology of interest and provide available real-world data, then the Real-Twin will generate relevant scenarios as well as the implementation of these scenarios in different simulators of XIL (such as traffic simulator VISSIM/SUMO, vehicle simulator IPG CarMaker/CARLA). Note that real-world data from users are optional for Real-Twin. If users do not provide any data, Real-Twin will use available data sets identified in this project to output scenarios. If users do provide data, for example, users want to study a particular corridor of a specific city and have real-world data collected from this corridor [1], then Real-Twin can synthesize the data to generate scenarios that can reflect this particular corridor. The objectives of this project are further identified and described in detail below.

Approach

1. Establish a unified definition of scenarios

The first and foremost objective of Real-Twin is to establish a unified definition of scenarios. We aim to establish a common language within the mobility research community to describe and characterize scenarios. To achieve this objective, we will engage with the research community to understand current usages of the terminology and gain inputs from existing projects and activities. Different agencies e.g., DOE, Environmental Protection Agency (EPA), DOT (CARMA, VOICES, etc.), industry, academia will be contacted to have comprehensive perspectives. A review of existing definitions will be conducted from literature as well as open standards (e.g., OpenSCENARIO). Then, a unified definition of scenarios can be established, and each element will be characterized.

2. Synthesize real-world data and application-based inputs for scenario generation

Realistic scenarios require realistic data inputs from real-world data sources. Real-world data, such as GIS data, real-time traffic sensors (e.g., cameras, detectors, probe vehicles), National Labs database, national data programs (e.g., DOT, EPA, and other agencies), and open-source data, contain useful specification and information of different scenery (roadway geometries, elevation, obstacles, etc.) and actors (vehicles, signal controllers, pedestrians, etc.). Moreover, evaluation of emerging mobility technologies often requires application-based inputs supplementary to the real-world data to synthesize and generate scenarios that are not yet entirely observable in the real-world. For example, high levels of vehicle electrification, connectivity, and/or automation are not yet a reality but attributes that characterize these emerging mobility technologies are required to be synthesized as inputs to the generation of scenarios. A streamlined workflow and relevant tools will be developed to process, quantify, and characterize real-world data as well as to synthesize application-based inputs to generate realistic and tangible scenarios for mobility technologies evaluation.

3. Generate real-world/synthetic scenarios ready for implementation in Real-Sim and/or other facility

Once a scenario is defined and characterized with data, the next research question is how to implement such a scenario into XIL. There is a need to identify current gaps in existing tools and develop workflows to develop new tools or add new features to existing tools to facilitate the implementation of different scenarios in various XIL simulators such as traffic microsimulation (VISSIM and SUMO) and virtual environments (IPG CarMaker and CARLA). Different simulators have their own specifications and formats on the inputs needed to define a complete simulation. Thus, even the same scenario defined in Real-Twin can be translated to different inputs formats for different simulators. We will first develop tools to make this translation process transparent to users and map scenarios into input formats for different simulators. Then we will develop tools to enable semiautomated/automated calibration so that scenarios simulated in these simulators can be calibrated to reflect reality. For external users with simulators that ORNL use (VISSIM, SUMO, CARLA, IPG CarMaker) and no additional real-world data, plug-and-play is expected when using Real-Twin and no further calibration is expected. When using software that ORNL use but with new real-world data user inputs, calibration is needed, but tools to implement and calibrate scenarios for a variety of simulators accelerate the calibration process. To work with other simulator(s), the semiautomated/automated calibration toolchain can be used for calibration.

4. Develop and discover metrics for calibrating and characterizing scenarios for use in scenarios population and search parameters for researchers

One integral element of Real-Twin is to identify metrics that help quantify and characterize the scenario generation capability. Specific metrics that enable objective evaluation and characterization of the scenario generation capability will be explored and developed to help guide the scenario generation process to produce unified and tangible scenarios that are suitable for evaluating a variety of mobility technologies based on real-world data and synthesized application-based inputs. We envision Real-Twin can generate scenarios for EEMS technologies that can be implemented in Real-Sim and other external facilities, significantly reducing the inconsistency and manual efforts needed in current scenario generation process. These identified and defined metrics serve as measures to populate and parameterize scenario elements from the indexed database so that users can be well informed when generating scenarios using Real-Twin.

Results

1. Real-Twin workflow

Based on the unified definition of scenarios established in FY22, the detailed Real-Twin workflow (Figure I.1.1.2) was developed. All the toolchains developed in Real-Twin will be open source and release for public use in later stage of this project (GitHub: https://github.com/Real-Twin). The workflow of Real-Twin streamlines the process of generating unified scenarios in different simulation tools. Real-Twin first ingests multiple user inputs (if any) and transforms them into a standard format to generate abstract scenarios that can be understood by both humans and machines. If any required abstract scenario component is missing, Real-Twin will automatically retrieve data from existing databases to complete the missing component. Then Real-Twin generates concrete scenarios that can be understood and imported into different simulation tools (e.g., SUMO, VISSIM, Aimsun). Finally, Real-Twin uses simulation results as feedback to calibrate and tune the simulation to ensure consistent and unified scenario generation.

2. Real-Twin scenario generation tools

Following the workflow shown in Figure I.2.5.2, scenario generation tools have been developed as a Python package. Each module of Real-Twin workflow is defined as a Python class in the tools with subclasses and functions that help streamline the process of generating traffic scenarios by automatically or semiautomatically producing critical elements of scenarios. The tools can take user inputs and generate abstract and concrete scenarios in well-defined formats so that they can be implemented into different microscopic traffic simulators. Four modules have been developed for the tools and are summarized below:

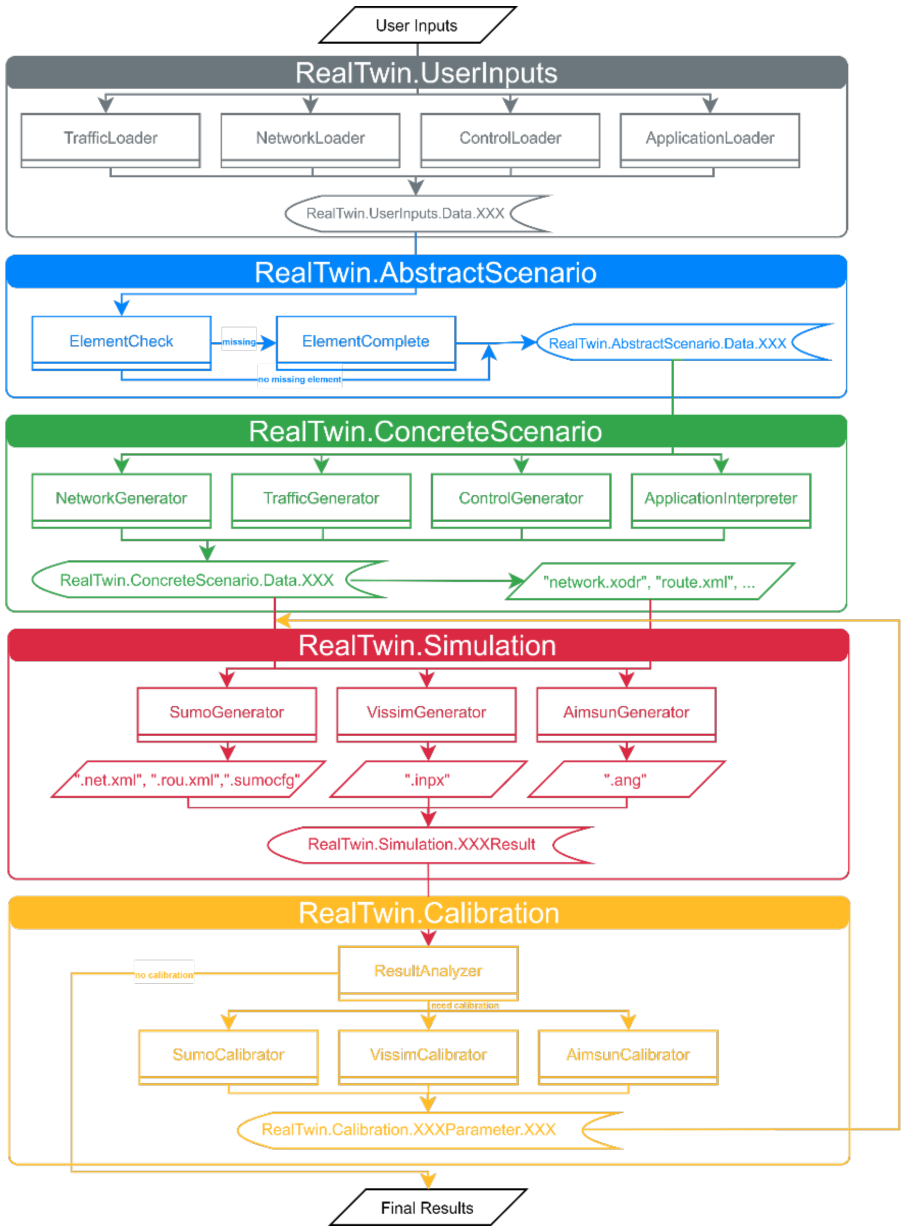

Figure I.2.5.2 Real-Twin workflow

a. RealTwin.UserInputs

RealTwin.UserInputs is a module for ingesting user inputs. This module reads user-supplied data and converts it into a format that Real-Twin can understand. Once converted, this data are stored in an intermediate variable called *RealTwin.UserInputs.Data* and passed along to the subsequent module in the workflow. The user input interface of Real-Twin is a YAML file that stores scenario parameters or data file paths. YAML, short for yet another markup language, is a lightweight human readable serializing language primarily designed to be easy to read and edit and thus is often used to create automation processes. An example of a YAML file that meets the minimum requirements for user input is depicted in Figure I.2.5.3.

```
Traffic:
   Volume: volume.csv
   TurningRatio: turn.csv
Network:
   NetworkVertices: (longitude1, latitude1), (longitude2, latitude2),
                    (longitude3, latitude3), (longitude4, latitude4),
Control:
   IntersectionControl: control.csv
```

Figure I.2.5.3 Example user input file for Real-Twin scenario generation tools

b. RealTwin.AbstractScenario

RealTwin.AbstractScenario is the module for generating the abstract scenario. Abstract scenario definition can be descriptive and is a direct transformation of user inputs into Real-Twin. An abstract scenario, created from *RealTwin.UserInputs* as shown in Figure I.2.5.2, is composed of four elements: *TrafficLoader*, *NetworkLoader*, *ControlLoader*, and *ApplicationLoader* that provide the four key components of an abstract scenario - Demand, Supply, Control, and Application.

c. RealTwin.ConcreteScenario

In the *RealTwin.ConcreteScenario* module, an abstract scenario is converted into a concrete scenario where every scenario element attribute is quantified and defined. A concrete scenario is composed of: 1) *NetworkGenerator* for network development, 2) *TrafficGenerator* for demand and route data generation, 3) *ControlGenerator* for traffic control generation, and 4) *ApplicationIntepretor* for development of technology application scenario. The technology application aims to enable users to generate concrete scenarios for the selected technology, such as AV or CAV. As a first step, the capability of generating AV scenarios has been developed. Based on an extensive literature survey, the key car-following, lane-changing, and other speed distribution related parameters and their values were identified for Krauss car-following model in SUMO and Wiedemann 99 in VISSIM. Based on the technology-specific parameters provided by users in the *RealTwin.UserInputs* file, the *ApplicationInterpretor* generates a concrete scenario with AV in the fleet. The generated AV scenario consists of a vehicle type for AV with corresponding driving behavior model parameters to represent it.

d. RealTwin.Simulation

RealTwin.Simulation module takes the concrete scenario definition and automatically implements the detailed scenario into different microscopic traffic simulators (e.g., SUMO, VISSIM, and Aimsun).

4. Scenario to XIL Simulators

In FY 2023, the process of generating scenarios into one set of commercial traffic microsimulation (VISSIM) and virtual environment (IPG CarMaker) was demonstrated and tested (Figure I.2.5.4). IPG CarMaker's VISSIM Interface was utilized to develop the co-simulation. The key steps included: 1) creating a new project in IPG CarMaker; 2) developing a road scenario in IPG CarMaker by importing the OpenDRIVE file and setting route maneuver for ego vehicle; 3) creating a test run to link the CarMaker scenario with the corresponding VISSIM file; and 4) setting ego vehicle maneuver based on simulation time. The VISSIM and IPG CarMaker co-simulation was developed on the VISSIM network generated by the Real-Twin tool. Figure I.2.5.4 shows the snapshot of co-simulation in IPG Movie. The speed and acceleration profile of the ego vehicle was collected based on the co-simulation. During this experiment, it is noted that the CarMaker and VISSIM co-simulation environment needs improvements to model realistic behavior such as: 1) parameter tuning of CarMaker vehicle for more realistic driving behavior; 2) improved perception and reaction time of the ego vehicle in response to presence of other VISSIM vehicles; and 3) ego vehicle's response to VISSIM signal indications. Currently, by choosing the ego vehicle start time and maneuver that is realistic and responds to VISSIM signal indications by following a VISSIM vehicle, these limitations are taken care of. In future, the differences in the ego vehicle speed and acceleration profile when using the co-simulation versus only VISSIM simulation will be evaluated. This is aimed to identify the key benefits of including vehicle dynamics in the microscopic traffic simulation scenario.

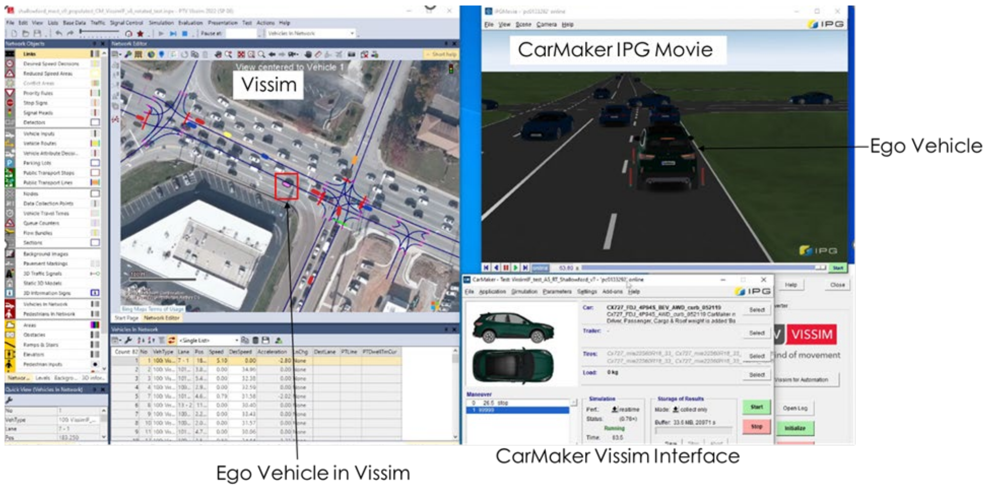

Figure I.2.5.4 IPG CarMaker and VISSIM co-simulation

Conclusions

As part of the FY 2023 effort, Real-Twin used the proposed definition and workflow to develop and expand tools to ingest real-world data sources into elements (e.g., road networks, vehicle data, signal, and detector data) and implement scenarios in different microscopic traffic simulators (SUMO, VISSIM, and Aimsun). Furthermore, the Real-Twin generated scenario in VISSIM was integrated with the commercial vehicle simulator IPG CarMaker to create co-simulation environment. In the next FY, Real-Twin project will develop (semi)automated calibration tools for scenario generation, improve and expand technologies being considered and covered by Real-Twin, continue to extend the capability of the Real-Twin tools to implement concrete scenarios into open-source simulators (e.g., SUMO+CARLA) and exercise the tools in various XIL simulations.

Key Publications

1. Shao, Yunli, Chieh (Ross) Wang, and Guanhao Xu. “A Paradigm for Consistent Connected and Automated Vehicles Traffic Microsimulation Across Different Toolchains.” In *International Conference on Transportation and Development 2023*, Austin, TX, 2023.

2. Saroj, Abhilasha, Guanhao Xu, Yunli Shao, and Chieh (Ross) Wang “A Comparative Workflow of Microscopic Simulation Software for Consistent Scenario Development.” In *103rd Transportation Research Board (TRB) Annual Meeting*, 2024. (Accepted)

3. Xu, Guanhao, Abhilasha Saroj, Yunli Shao, and Chieh (Ross) Wang. “RealTwin: An Automated Scenario Generation Tool for Microscopic Traffic Simulation.” In *103rd Transportation Research Board (TRB) Annual Meeting*, 2024. (Accepted)

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I.2.6 Modeling Connected and Automated Vehicle Compute Power (Sandia National Laboratories)

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Start Date: April 1, 2022 End Date: March 31, 2024
Project Funding: $300,000 DOE share: $300,000 Non-DOE share: $0

Project Introduction

An improved understanding of the energy profile of AVs across speed, driving conditions, vehicle type, and the nature of the trip is needed to accurately estimate the energy requirements for current and future AV systems. Understanding and ultimately reducing the energy consumed for computing in a highly automated vehicle is a complicated task. The instantaneous power usage of AV on-board computing systems will vary as a function of vehicle speed, vehicle type, collective driving conditions (related to the operational design domains), and the level of automation. This time-dependent variation of power means that the energy allocated to propulsion versus computing depends on the nature of the trip. Computing profile information is used to correctly predict vehicle power, range, and energy usage in higher level models used in the SMART Mobility Consortium.

Objectives

This project will develop a simulation framework to evaluate the energy consumption of computing for AVs. The framework will take as an input descriptions of the onboard compute hardware, a description of the processing pipeline to be run on that hardware, and a description of a trip. Internally, the simulator will compute the energy consumption for each second of the trip to examine how energy consumption changes based on the driving conditions. The resulting compute-energy timeline can be combined with the output of NREL FASTSim [1], an existing modeling of vehicle energy to examine the impacts of AV compute demands on vehicle performance. This analysis will help inform future work on the importance of compute energy efficiency for AVs and help identify potential areas for optimization and future research. Additionally, the full simulation framework, including a test-harness for use with FASTSim, will be open-sourced to assist future researchers.

Approach

The developed energy estimation tool uses a data movement-centric energy model like the approach proposed by prior computer architecture modeling tools such as Timeloop [2]. This modeling approach proceeds in three basic steps.

1. Using a dataflow graph constructed from the user-specified algorithm descriptions, statically schedule algorithms across user-specified devices and memories using a ‘greedy’ algorithm.

2. Determine data movement and compute events for the static schedule. For instance, loading 10 MB of data for a neural network into a memory with a 2MB capacity would generate five 2 MB load events.

3. Multiply event counts by user-specified energy consumption per event to determine total compute energy for the set of algorithms.

These steps are repeated for each second of the simulated trip to capture time-varying and scenario-dependent energy consumptions. For instance, a vehicle arriving at a traffic light may consume additional compute energy due to the greater number of other objects (e.g., vehicles, pedestrians) the system needs to contend with.

The developed model can also be run within a test harness which uses NREL FASTSim to produce a vehicle energy consumption estimate for the trip allowing users to assess the effects of compute energy consumption on total vehicle energy consumption for the trip.

Results

Figure I.2.6.1 shows an example output from the developed simulator. This example considers a low-speed urban scenario, potentially the most challenged from a compute-energy perspective due to the high number of potential obstacles and low vehicle speed. The low-speed means reduced energy is used for movement; therefore, algorithms with a relatively fixed cost such as object detection can consume a more significant fraction of total system energy. This example uses the empirically validated 2016 Chevrolet Bolt model from FASTSim and simulates a computer system consisting of a pair of Nvidia A100 GPUs processing input from six cameras. The simulated computer system is running an object detection kernel based on the You Only Look Once (YOLO) v5 neural network [3], and a per-detected-object trajectory prediction kernel based on a combination of convolution and recurrent neural network layers [4].

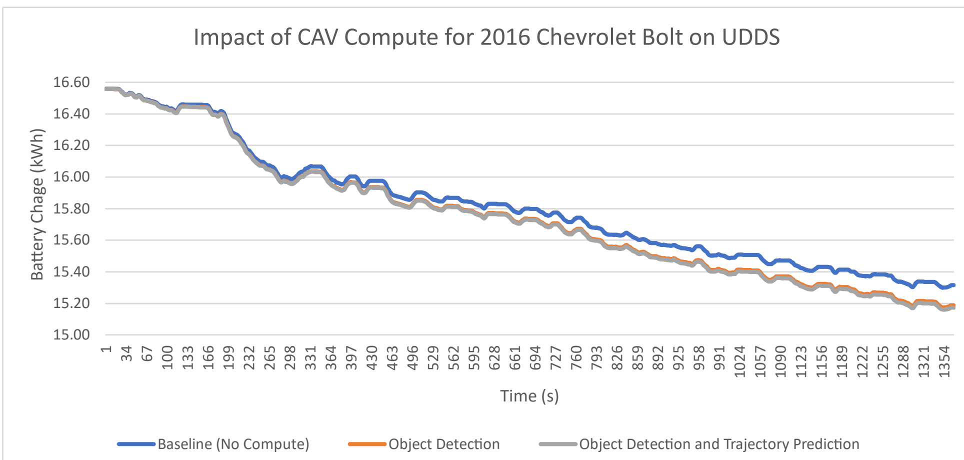

Figure I.2.6.1 Example simulation output for a 2016 Chevrolet Bolt performing object detection and prediction trajectory prediction for other vehicles over the EPA UDDS.

This result shows that in a low-speed environment automation enabling hardware and algorithms can consume a significant fraction of overall vehicle energy. In this example, the object detection kernel increases total vehicle energy consumption by over 10% on the simulated trip. Moreover, this example shows only two relevant kernels, selected based on broad applicability and research interest such that multiple options are available for simulation, while a full AV system will need multiple additional kernels. This result therefore represents an optimistic floor for the compute impacts of automation enabling hardware.

Conclusions

AV systems require a significant increase in the amount of compute power in a vehicle. To effectively optimize this hardware, new research tools are needed to identify the scenarios where compute will significantly reduce total vehicle energy efficiency. In this project we have developed the first tool to connect vehicle efficiency and AV compute cost. This creates a baseline for future research and a framework that can be extended with higher fidelity models to explore a wide range of questions related to AV computing.

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I.3 AI, HPC, & Data Analytics

I.3.1 Scaling up the Real-Time Data, Simulation & AI, and Control for Optimizing Regional Mobility in the United States (Oak Ridge National Laboratory, National Renewable Energy Laboratory)

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Project Funding: $0 DOE share: $0 Non-DOE share: $0

Project Introduction

Highway congestion wastes over three billion gallons of fuel each year and causes seven billion hours of lost productivity. Highway congestion costs freight movers approximately $63 billion dollars per year, ranging from $5,600–$30,000 per truck (and is increasing). Research has shown the ability to introduce near-real time traffic monitoring and adaptive signal control (including small numbers of connected vehicles) can yield up to 30% reduction in congestion. Deploying this approach at a regional scale, that has high-volume and transient traffic, extreme data volumes, and potentially 100,000 vehicles, sensors, and control devices requires HPC. We created a "digital twin" of the Chattanooga region with simultaneous pairing of both the virtual and physical world providing real-time situational awareness. This digital twin will be the basis for a cyber physical control system with high-speed bidirectional communication and control of the highway infrastructure and connected vehicles in the ecosystem to achieve a 20% energy savings in a region. If successful, the results of this project could be replicated region-by-region to commercialize the approach across the entire U.S., so that over the next 10 years, this project accelerates a reliable intelligent mobility system implementation to reduce overall mobility-related energy consumption by 20% and recover $100 billion of lost productivity in congestion.

The availability of real-time data from vehicles and the deployment of supporting infrastructure such as high-speed fiber networks have opened up an unprecedented opportunity to bring together high-performance computing, advanced mobility simulations, and existing transportation expertise to create a platform that could have a decadal impact in transforming regional mobility in the United States. We propose to optimize the movement of both people and freight in and around Chattanooga, Tennessee, a representative urban/suburban region, by leveraging high performance computing, data analytics, and machine learning. Near real-time insights provided by the integration of data from emerging mobility technologies and services can inform all phases of strategic planning, design, operation, modernization, and decommissioning of ageing/legacy systems. Lessons learned and capabilities developed and deployed for regional mobility can be applied to optimize mobility nationally deploying region-by-region.

Objectives

The project drives energy-efficient mobility science and technologies from early stage HPC-based R&D through demonstration to commercialize the optimization of mobility, energy efficiency, and productivity in a regional traffic domain. Although there is emphasis in this project on real-time traffic management, the models and data will be immensely beneficial for planning transportation infrastructure. With the proper approach, preparedness for future population of CAVs will be achieved, yet benefits will come in the nearer term from accelerated intelligent infrastructure impact on the operation and movement of conventional vehicles. The project will develop and deploy approaches and capabilities that are scalable to larger and more densely populated regions, ultimately to the national scale.

A key goal is to demonstrate the ability to deliver a 20% decrease in energy consumption through the Real-time Digital Twin and Cyber Physical Control of the transportation system.

Approach

Current Chattanooga Digital Twin (*CTwin*) research has delivered a regional-scale, open, scalable, real-time situational awareness platform that is unique for VTO. Metrics based on industry standards (MAP-21, Automated Traffic Signal Performance Measures) have been formulated to compute energy usage estimates, regional speed, volume, and fuel used, as well as derive travel time reliability and percent stops on red, besides others. Advanced data science approaches on real-time feeds data-driven discoveries of incidents in roadside radar sensor data which resulted in an invention disclosure. This research has furthermore demonstrated an innovative use of low-resolution roadside camera data to produce truck/freight counts using a highly parallel real-time computer vision workflow. Mesoscopic simulation of the regional transportation system and microscopic simulation for small, targeted areas were developed to enable the representation and evaluation of different traffic control algorithms before deployment. The implementation of a cyber-physical control in different areas Chattanooga has resulted in almost 40% delay reduction that realized more than 16% energy savings in the field.

The current *CTwin* effort has built the necessary collaborations, gained operational insights, and has developed the technological base to deliver a demonstration of the envisioned 20%+ energy savings. This work expands to an inter-region scale, real-world, data-driven capability to the VTO portfolio. The *CTwin* effort is synergistic with several VTO funded activities in the Atlanta - Chattanooga - Nashville - Knoxville area and the performers are in close communication with the proposal team. Data ingress features in *CTwin* also benefit the SMART 2.0 V2I project with the city and Toyota. The proposed work solidifies and unites these partnerships for the next stage of real-world impact across a larger region.

The goal of this proposed research is to employ AI and HPC methods to geographically and computationally scale up *CTwin*, to accomplish 20%+ energy savings across city streets and freeways for passenger traffic, freight, and connected vehicles. The research has delivered:

1. Inter-regional geospatial situational awareness with real-time and historic data feeds from transportation departments of Tennessee, Georgia, and City of Chattanooga, fused with real-time and historic data feeds from FreightWaves, TomTom, and Wejo.

2. Transformational data-driven insights using AI for the performance assessment of all signalized intersections in the region, the prediction of future traffic states, the detection of incidents in real-time, the derivation of high-resolution near real-time truck/freight movement, and energy-based performance metrics.

3. Previously regional mesoscopic simulations were scaled-up to include sections of Georgia of interest. Localized microscopic simulation were also extended to represent traffic from downtown Chattanooga through the East Chattanooga area. The microscopic simulations were also calibrated to provide a more realistic testbed to evaluate real-time traffic signal control algorithms before deployment.

4. In progress: Expansion of the existing single corridor control strategy to obtain an integrated regional mobility control solution using AI that encompasses downtown Chattanooga and extends through East Chattanooga to connect to the initial testbed of Shallowford Road in the Northeast. This effort will include the evaluation of different signal control strategies, and real-time field experiments to demonstrate the efficacy of the methodology.

Additional benefits of the work include reduction in time wasted in traffic and lost productivity; reduction in fuel usage, fleet wear and tear, and emissions; dramatic improvement in response time for traffic incidents; significant financial savings and improvements in infrastructure upkeep, and transformational observability across disparate vendor systems.

Results

We now describe the results and progress made by the final quarter (first quester [Q1] of FY 2023) of the project:

Milestone: Deploy the control algorithm in the field for 85% of hours for 3 weeks. Complete analysis and evaluate the performance of the proposed control algorithm.

We ran a field experiment from October 8, 2021 to November 1, 2021 for 24 hours a day, making it the longest live, automated experiment we have conducted thus far along the Shallowford Road corridor. The corridor was also extended to include Lifestyle Way and Gunbarrel Road. After compiling the TomTom data for the experiment along with the previous two years of historical data, we selected from January 2021 up to October 8 to be our comparison group. Using the energy pipeline, we did our analysis to see where and when we most improved the traffic flow and energy consumption.

Key Activities

The following key activities were part of the abovementioned milestone:

1. An average of 4% reduction in "average time spent waiting" across all days of the week, time-of-days, and six intersections;

2. A maximum of 18% reduction in average time spent waiting at the "Shallowford Rd & Napier Rd/Hamilton Place Blvd" intersection;

3. Changes in performance vary by time-of-day. Significant improvements were confined mostly to off-peak periods during early morning hours (5 to 8 am) and late evening hours (6 to 9 pm); and

4. Benefits vary by day of the week. Mondays have the highest, whereas Fridays see the least improvements.

We also scaled up our control and ran an experiment on March 27-30, 2023 at 24 intersections in downtown Chattanooga, Tennessee during the afternoon rush hour using real-time GridSmart data and model predictive control (MPC) to improve traffic flow efficiency, with initial setup and split validation (see Figure I.3.1.1). The objective was to optimize signal timings at 24 downtown Chattanooga intersections during afternoon rush hours using real-time data and MPC, while assessing traffic flow improvements.

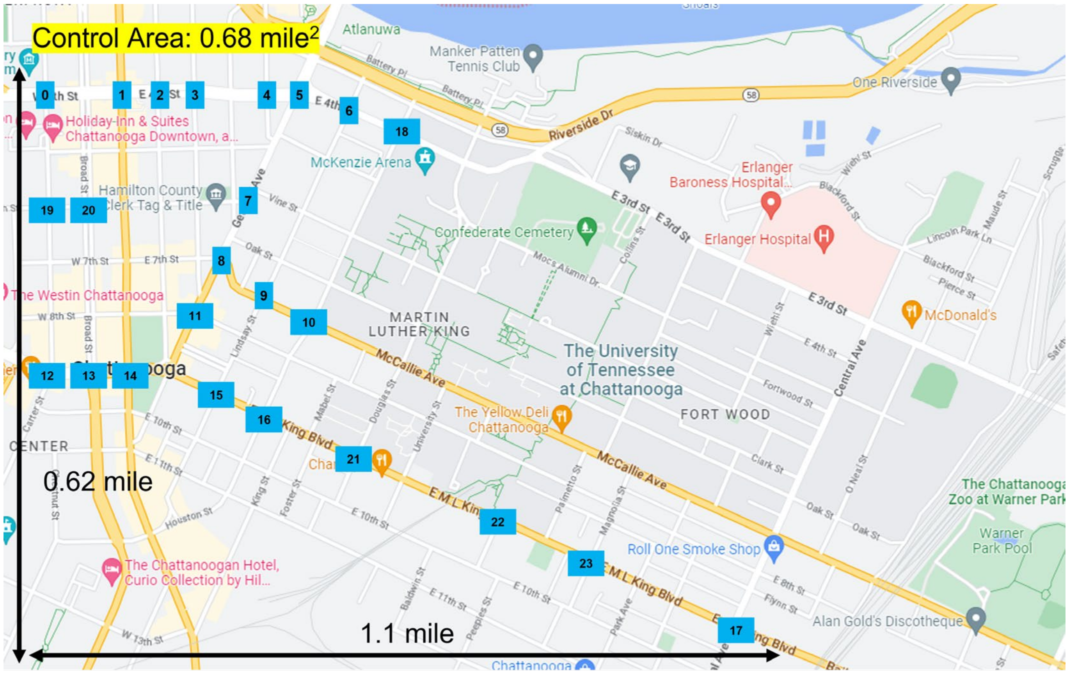

Figure I.3.1.1 Scaled up the experiment at 24 intersections in downtown Chattanooga, Tennessee

Key Activities

The following key activities were included in this quarter.

1. We scaled up our control to optimize traffic signal timings at 24 intersections in Downtown Chattanooga, Tennessee;

2. We leveraged real-time data from GridSmart (Measurement) in combination with MPC techniques to enhance signal timing;

3. Our task involved calculating the optimal split for each phase at these controlled intersections, aiming to improve traffic flow;

4. During a four-day period from March 27 to March 30, Monday through Thursday, we conducted experiments during the afternoon rush hour, from 15:30 to 17:30. The first day, March 27, was utilized as a dry run experiment, focusing on setting up parameters and checking for minimum and maximum split violations; and

5. Results showed that the improvement in the arrivals on green (which is the percentage of vehicles that arrive at the intersection during green time) ranged from 6.6% to 16.9%.

Conclusions

The above sections summarize activities in the project in FY 2023. The third year of development of the various activities delivered key artifacts of situational awareness, data insights, simulation estimates of energy savings, and cyber-physical actuation of on-street hardware. The team prepared for the final quarter, which focused on the execution of large-scale cyber-physical control experiments throughout much of Chattanooga. The team furthermore emphasized stakeholder engagement in order to understand the long-term needs beyond the scope of the current project. Through these engagements, the project team learned a lot from stakeholders, and they are excited to pursue and mature the activity to deliver significant energy savings for the region during *CTwin* 2.0 and beyond.

Key Publications

1. Tong Liu, Hong Wang and Zhong-Ping Jiang, "Data-Driven Optimal Control of Traffic Signals for Urban Road Networks", IEEE Conference on Decision and Control, pp. 844 – 849, 2022.

2. H. Xu, A. Berres, J. New, and C. R. Wang, "Toward a Smart Metaverse City: Immersive Realism and 3D Visualization of Digital Twin Cities", Advances in Scalable and Intelligent Geospatial Analytics: Challenges and Applications. CRC Press, 2023.

3. J. Park, T. Liu, C. Wang, A. Berres, J. Severino, J. Ugirumurera, A. Kohls, H. Wang, J. Sanyal, and J. Jiang, "Connected Traffic Signal Coordination Optimization Framework through Network-wide Adaptive Linear Quadratic Regulator-based Control Strategy", submitted to ASCE Journal of Transportation Engineering, Part A: Systems, 2023.

Acknowledgements

The *CTwin* team would like to thank our partners: the City of Chattanooga, Tennessee Department of Transportation, Georgia Department of Transportation, and FreightWaves for their continued support of this project. We would like to especially thank the City of Chattanooga for the support and excellent collaborative work on the cyber-physical control field experiments. Finally, the team would like to thank DOE Vehicle Technologies Office for funding this work, and Prasad Gupte and Erin Boyd in particular for their mentorship and fruitful discussions.

I.3.2 Big Data Solutions for Mobility Planning (Lawrence Berkeley National Laboratory, Argonne National Laboratory)

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Start Date: January 1, 2023 End Date: December 31, 2023
Project Funding : $870,000 DOE share: $870,000 Non-DOE share: $0

Project Introduction

The Big Data Solutions for Mobility Planning project was focused on using data science and DOE National Laboratory high-performance computing resources and expertise to enhance understanding of urban-scale transportation dynamics and develop strategies for significantly improved transportation system planning and operations with a focus on energy, congestion reduction and real-time situational awareness. We took a data driven approach: implementing large-scale ML/deep learning (DL) methods for high-value applications as well as integrating real-world data into AI-enabled, high-speed, urban-scale transportation network parallel-discrete event simulations (PDES). Our focus was on optimizing mobility, energy, productivity, regional economics, and quality of life in our cities by increasing mobility system efficiency, reducing cost, reducing fossil fuel use and increasing the effectiveness of transportation. This Phase 2: Closeout project focuses on the final objectives of the project: to develop a machine learning surrogate model for the Mobiliti simulation so that it can be delivered on traditional computing architectures, and to assess the current state of the data ecosystem that serves the mobility sector in order to understand how Mobiliti can integrate into and support the design of a robust, transparent and secure future data ecosystem.

Objectives

Task 1: Developing Machine Learning Surrogate Models for Regional Scale Transportation Network Models

This project's core objective is to integrate a graph-based, deep-learning system and PDES methods for transportation modeling for the purpose of building machine learning surrogate models. The approach draws on work completed for the DOE EERE funded, Big Data Solutions for Mobility Planning. It leverages the capability of the Mobiliti [1], [2], [3] platform to run regional scale traffic simulations in significantly lower compute times than traditional tools. With Mobiliti, traffic dynamics for metropolitan regions can be generated in a matter of minutes. For example, the San Francisco Bay Area with a road network of ~1 million links with ~19 million trips representing ~7 million drivers and ~4 million truck trips, can be run in approximately 3 minutes on DOE supercomputers. Large datasets that predict speeds and flows for all links, travel times for trips and trip level fuel use are a result of each run. Because the scenarios run in minutes, with appropriate development of the input scenarios, this capability can provide a large amount of training data for a graph-based, deep-learning model to learn and estimate the dynamics of the road network. The BDSM project's past work in developing graph-based, deep-learning models can be leveraged to develop surrogate models - models that embed the learned dynamics of the road network - that run on traditional computer architectures.

Task 2: Data Ecosystem Design for Future City Planning and Operations

This project's core objective is to provide a perspective on a future state transportation data ecosystem that can provide the greatest collective benefits to all relevant stakeholders. We seek to engage and collaborate across relevant parties to understand their motivations and to synthesize the information with consideration to any risks or downstream impacts. The goal is to assist policymakers within cities, regional agencies, DOTs, and private organizations to align on a consistent approach to measuring, analyzing, and using spatial and temporal transportation data. Mobility as a field greatly benefits from economies of scale and scope in planning and execution, which is best enabled through greater cross-talk and integration. This consistent approach can then inform downstream policy, planning and product decision-making to ensure that there is greater integration across the landscape to improve outcomes in transportation efficiency, equity, and sustainability.

Approach

Task 1: Developing Machine Learning Surrogate Models for Regional Scale Transportation Network Models

The project is partitioned into four major research and development tasks. Task 1 addresses the task of generating simulation results of different traffic scenarios of interest. We focus on detecting different traffic patterns and predicting traffic demand for a large variety of traffic scenarios. Task 2 addresses developing surrogate models with the new capability of learning and predicting real-world urban traffic dynamics. To this end, we will study how heterogeneous graph neural networks can be used for traffic state prediction in an urban setting. Tasks 3 and 4 focus on improving the robustness of our existing graph neural network (GNN) so that a continually learning system can be developed. We leverage the ANL Deep Hyper software for hyperparameter search and develop methods for sequential learning so that the model adapts to real-world changes over time.

Task 1.1: Data-Driven Travel Demand Model Improvement

In training our surrogate models, we pursue a supervised learning approach where data collected from the regional traffic simulation is used as the training data. The current 24-hour Mobiliti simulation generates network dynamics based on predefined origin-destination trip information for a 24-hour period. In order to generate more behavioral diversity in the trip demand and also to have more variable traffic dynamics across the network, we seek to intelligently create perturbations to the set of trip plans.

Demand models only generate traffic demand for a single "representative" day, which is not sufficient to stimulate all types of network conditions and congestion patterns that may be of interest to the traffic modeling community. In contrast, we focus on enhancing our understanding of the current demand model and uncover different types of traffic behavior. Based on this traffic behavior analysis, one can create trip plans that are later used in training models for atypical extreme scenarios (e.g., evacuation, traffic accidents). The training data set must include examples of the network behavior under these atypical scenarios in order for the surrogate model to make accurate predictions under those conditions. In order to obtain different simulation data that can contains sufficient behavioral diversity, we consider various options such as (1) adding midpoints in the routing algorithm, (2) locally increasing traffic demand at certain origin nodes to induce more traffic volume on arterials and lower-class roads, and (3) creating extreme scenarios where the traffic is guided toward major evacuation points.

Task 1.2: Surrogate Models for Traffic Prediction on Complex Networks

Most traffic forecast models consider the traffic network as a homogeneous graph where the traffic dynamics of any node in the network share similar patterns and behaviors. However, the way traffic dynamics are interrelated is significantly different between different types of locations, e.g., a highway/ramp interactions vs. street intersections. Several attempts have been made to analyze heterogeneous graphs for node classification, link prediction, etc. We are developing a heterogeneous GNN to capture multiple types of traffic dynamics of our simulation model for the time series prediction tasks. Using the training (simulation) data obtained in first task, we train and test these models for typical and atypical traffic conditions.

Task 1.3: Optimizing Neural Networks Surrogate Models
Designing neural network based surrogate models and tuning their hyperparameters often relies on trial-and-error methods including the existing meta continual learning approaches. The results of these methods lead to poor generalization and deterioration in robustness of the model. Instead, we leverage our recent advances in DeepHyper, a scalable open-source package for AutoML. It is composed of two components: neural architecture search (NAS) and hyperparameter search (HPS). NAS can be used to develop neural network models from the given data based on a user-defined high-level search space. This goal is achieved through two search methods: distributed reinforcement learning, where multiple agents generate different neural architectures, evaluated by the worker nodes in parallel; and regularized evolutionary methods, where a random set of neural architectures are iteratively improved through genetic operators such as mutation and crossover. HPS is used to improve the existing models by fine-tuning their hyperparameters achieved through an asynchronous Bayesian optimization method that consists of sampling a number of hyperparameter configurations and progressively fitting a model over the hyperparameter configuration accuracy metric space.

Task 1.4: Continually Learning Surrogate Models
The development of surrogate models requires centralized training of neural network models on HPC resources. The trained model is then deployed on moderate-scale computing resources, such as a desktop or laptop, for real-time inference and execution. The inflexibility arising from the typical separation of training and execution, however, impedes the effectiveness of the surrogate models. Specifically, it is often not possible to collect or generate all the data required for training, and the data changes over time due to new traffic patterns and transportation infrastructure upgrades. Consequently, surrogate models need to be constantly re-trained to take data changes into account after deployment. However, retraining is computationally inefficient and affects the model's ability to quickly adapt to new data. Whereas, retraining only on the new data after deployment leads to catastrophic forgetting, wherein the surrogate model forgets the learning from the past. In our previous work, we developed a new theoretically sound game-theoretic approach to continual learning of neural network surrogates.

Task 2: Data Ecosystem Design for Future City Planning and Operations
Our project approach is divided into four main focus areas: evaluating existing examples, identifying successful design characteristics, determining a gap analysis and existing stakeholders, and proposing a future pilot ecosystem.

Task 2.1: Existing Examples
Given the state of disruption in the transportation sector and the increasing level of connectivity year-over-year, we have a need to understand pivotal technology standards from the past, their journey, and the societal outcomes that standardization enabled. If we learn from history, it will help us anticipate outcomes and avoid potential pitfalls when galvanizing new technology for public access. Within this focus area, we will implement the following task sub-activities: Identify three to five public domain technologies, standards, and ecosystems for review which are most relevant to the proposed data ecosystem (e.g., GPS, cellular bands, Wi-Fi standards); Conduct meta-analysis on historical context, published literature, and outcomes; and Synthesize findings and highlight lessons, methods, and risks for consideration.

Task 2.2: Current State Ecosystem Review and Successful Design Characteristics
The current transportation data ecosystem has multiple entities such as technology firms (Google, Apple, HERE Maps, etc.), universities, and government agencies developing systems to manage and organize the data. There is an abundance of data ranging from driver behavior, traffic, weather, accidents, vehicle messages, traffic signals and road characteristics, however, there is no clear understanding of how to best utilize and process the data. An investigation into the current ecosystem and the entities involved is required in order to maximize Mobiliti's benefits along with and understanding the theory and design considerations behind an ecosystem of this scale. The task entails: Quantifying the impact and value Mobiliti can provide within the current ecosystem; Researching the current entities in the ecosystem to understand how Mobiliti may integrate and provide value; Researching alternative data ecosystems and data supply chains to maximize benefits for all entities involved in the system; Researching design and theoretical considerations for developing a system-of-

systems data ecosystem at Mobiliti's scale; and Researching Mobiliti's theoretical position and added value in the current ecosystem.

Task 2.3: Stakeholder and Gap Analysis
In order to reach our end goal of developing tools that support cities, regional agencies and the DOTs in providing economically viable, safe and healthy cities, we must have a deep understanding of the public and private stakeholders impacting/ transportation networks. This will require that we not only take inventory and perform a deep dive of the current ecosystem but forecast the future state and perform a gap analysis. We will perform competitive landscape analysis on the following types of stakeholders: shipping companies; large retailers; people movers (e.g., Uber, Lyft, Google Maps, Apple Maps, Waymo, Tesla); city/regional managers and planners; and public and private financiers (e.g., DOE and DOT, venture capital, private equity, equity research). After gaining an understanding of the major stakeholders across the transportation landscape, it will be important to engage in holistic discussions with these stakeholders to further define their current and future motivations, pain-points, as well as data inputs and outputs. Initiating these conversations will be crucial for designing such a complex tool that acts as a comprehensive system of systems and will allow us to refine our current model of transportation-related generated data.

Task 2.4: Future State Pilot Ecosystem and Data Supply Chain
The current ecosystem is still developing and there are minimal if any industry standards in place to organize the data and data supply chain. In order to envision an improved ecosystem, we'll need to research how an ideal ecosystem would operate. This task entails: Researching the data supply chain system and outlining the data supply chain from initial phases of collecting raw data to a processed end product; Interviewing stakeholders to understand the data supply chain and how an ideal ecosystem would operate to maximize benefits to all entities involved; Conducting a comparable ecosystems review; Developing a comparison of the current ecosystem and an ideal ecosystem; Assessing and highlighting Mobiliti's position and outline its value proposition; Defining the end product(s) of the data supply chain and possible stakeholders interested in the output or parties that could benefit from the output; Defining the data input(s) of the data supply chain, identify possible stakeholders to partner with Mobiliti and outline the benefits provided to aforementioned stakeholders; researching APIs and how data will transfer from one state to another in the data supply chain; and researching new entities (e.g., microtransit, micromobility, freight, rail companies, real estate developers) that may enter the ecosystem and their role.

Results

Task 1: Developing Machine Learning Surrogate Models for Regional Scale Transportation Network Models

Task 1.1: Data-Driven Travel Demand Model Improvement
The core focus of this task is to create a training dataset for our surrogate model development. Using our simulation system, we must generate sufficient traffic dynamic patterns for the machine learning model training. We synthesized multiple traffic demand profiles as input to the simulation system and recorded the corresponding output traffic time series. To create traffic patterns for every location in the network, we need to develop a routing algorithm that satisfies the following two requirements:

(1) It can spread the vehicles over the whole network so we can observe traffic patterns in every location of the network and,
(2) It will not cause extreme traffic congestion (i.e., deadlock), ensuring that the vehicle's dynamic movements can be observed.

We first adopted user equilibrium traffic assignment as our simulation routing algorithm. We observed that many small-capacity lanes were underutilized, and we could not capture sufficient traffic patterns of them. To overcome this barrier, we modified the parameters of the speed-volume function. The results show that our proposed parameters effectively help us send vehicles to the underutilized links under the framework of user equilibrium traffic assignment. The routes derived by the routing algorithm of different parameters are shown in Figure I.3.2.1.

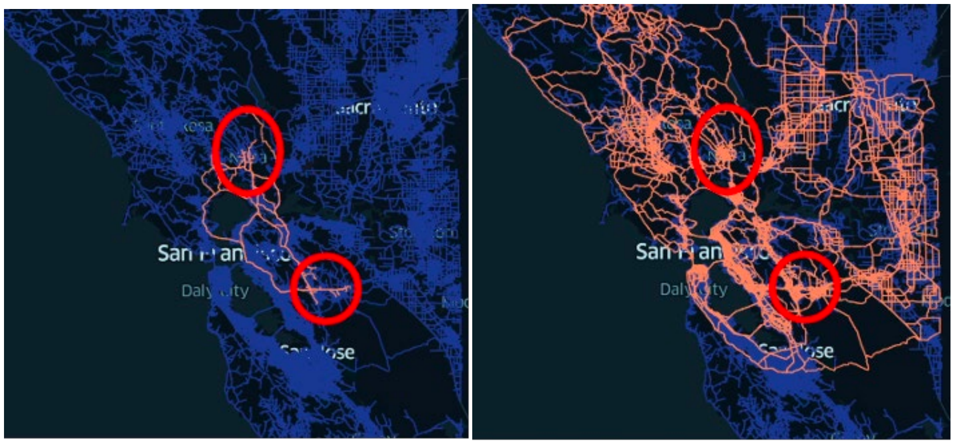

Figure I.3.2.1: (left) Route visualization of the simulation results with default parameters, (right) route visualization of the simulation results with proposed parameters of the speed volume function are shown as orange paths. Regions of the red circles are the traffic demand zones.

We subsequently adjusted the vehicle routes with the technique of dynamic re-routing to alleviate this deadlocking. As a result, we successfully created multiple traffic dynamic patterns with significantly reduced numbers of deadlock links. The deadlock links of our simulation results with and without the re-routing techniques are shown in Figure I.3.2.2.

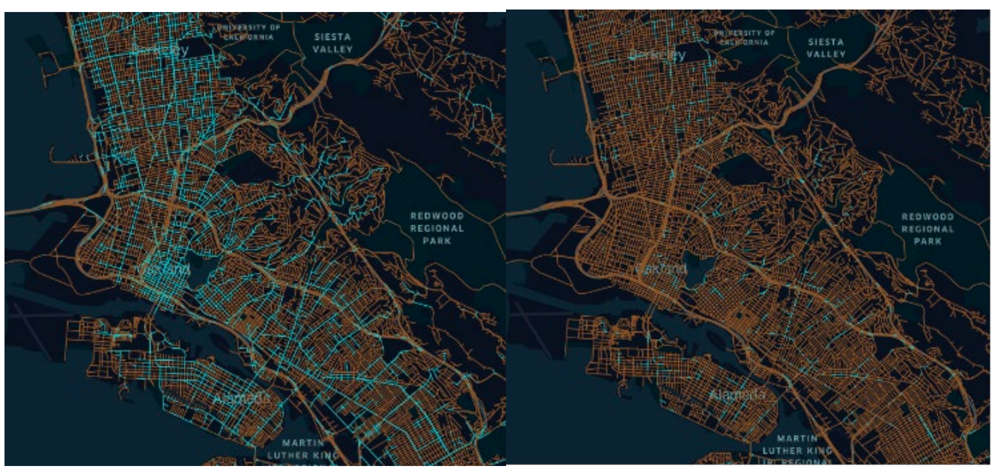

Figure I.3.2.2: (left) Deadlock links in blue without rerouting, (right) deadlock links with rerouting.

Task 1.2: Surrogate Models for Traffic Prediction on Complex Networks

We developed a surrogate model to capture traffic dynamics of our simulation model for the time series prediction tasks. The surrogate model uses time, origin, and destination demand data, which aids in forecasting the state of individual links (e.g., traffic flow, speed). While the Diffusion Convolutional Recurrent Neural Network (DCRNN) model with a mean absolute error (MAE) loss function adequately predicted average speed, it struggled with capturing specific perturbations in speed. To address this issue, we employed a DCRNN model equipped with a quantile regression loss function. This model aims to capture variations in data by accurately representing the upper and lower quantiles. The model displayed a satisfactory performance, achieving an MAE of 0.25 for speed prediction on 54,733 units. Notably, the prediction was not simply a mimicry of the input data; it was able to accurately follow significant speed variations. In addition, we implemented a system to quantify uncertainty for lower class road links. To achieve this, we assembled a group of models and assessed the epistemic uncertainty using the variance of their average prediction. Through uncertainty measurement for different road classes, we were able to identify areas where additional training data is needed. This is instrumental in refining the model and enhancing its predictive capabilities.

Task 1.4: Continually Learning Surrogate Models

Traffic dynamics are dynamic entities, continually evolving due to changes in traffic patterns and upgrades in transportation infrastructure. As such, surrogate model needs to be persistently updated and re-trained to accommodate these changes post deployment. In response to this, we are in the process of developing a continual learning mechanism for surrogate models. We are integrating a continual learning framework with our surrogate model (DCRNN). We frame continual learning as a sequential learning challenge where our goal is to minimize a cost function integrated over the entire lifespan of the model. We employ Bellman's principle of optimality to reformulate the continual learning problem. The new goal is to minimize the sum of the catastrophic forgetting cost for the previous data and the generalization cost for the new data. In our approach, we calculate the generalization cost by training the model on new task data and then evaluating its performance. Conversely, we compute the catastrophic forgetting cost by evaluating the model performance on the task memory (i.e., previous tasks) after it has been trained on new tasks. We iteratively minimize the generalization and catastrophic forgetting costs for a predefined number of iterations. This method allows us to establish a balance between the two, optimizing the performance of the model.

Task 2: Data Ecosystem Design for Future City Planning and Operations

In the first deliverable of our ecosystem review, we sought to build out an understanding of the transportation data ecosystem and frame a definition of the data domains and segments represented to shape stakeholder interviews.

Establishing standards: Much of today's society, not to mention the transportation landscape, is built upon the GPS and the Internet, two publicly available standard technologies. While their benefits are enjoyed by many and the standardization enables connectivity across the world, both technologies started as military projects designed to provide the US an edge in global conflict. GPS was designed for both military and civilian navigation, however, its public access was spurred by the Korea Air 007 incident. It was initially provided with a lower fidelity level than military applications, with full fidelity provided in 2000 by Bill Clinton enabling widespread economic benefits. In 2022, the U.S. government requested $91.8 million to maintain and enhance the GPS system for civilian transportation purposes, a bargain in context of what it enables from a civilian perspective. For the Internet, it began as a military project (ARPANet) in the 1950s and 1960s to transfer confidential research and the Internet leverages a wide range of open standards to enable interconnectivity across the network. Some of the most important open technology standards used on the Internet include: The Internet Protocol Suite (TCP/IP); The Domain Name System (DNS); The Hypertext Transfer Protocol (HTTP); The Secure Sockets Layer (SSL)/Transport Layer Security (TLS): These standards were widely adopted for a number of reasons. First, they are open, which means that anyone can use them without paying royalties. This made them more affordable and accessible to a wider range of developers. Second, they are well designed and have been thoroughly tested. This makes them reliable and efficient. Third, they are supported by a large community of developers, which means that there is a lot of documentation and support available.

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I.3.3 Applying Artificial Intelligence (AI) Based Signal Coordination and Controls for Optimized Mobility for the Nimitz Highway and Ala Moana Boulevard Arterial (Oak Ridge National Laboratory)

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Start Date: February 1, 2021 End Date: August 31, 2023
Project Funding: $2,000,000 DOE share: $2,000,000 Non-DOE share: $0

Project Introduction

a) Formulating Artificial Intelligence (AI)-Empowered Signal Control Optimization: The relationship between signal timing at intersections and the traffic flow is generally of unknown dynamics and is random in that at a particular time, the number of vehicles on the road is random [1] – [4]. This constitutes a dynamic and unknown stochastic system, and its modeling is generally difficult to perform using first-principle approaches. The system is a stochastic dynamic system if in the continuous-time domain, its solution is obtained using partial differential equations with random boundary conditions. The solution for such a complicated model is rather difficult to obtain and must frequently be solved using high-performance computing, which generally cannot be used for real-time control design. Therefore, data-driven modeling methods—in particular, those widely used in AI technology—need to be employed to establish simple dynamic models between signal control and traffic flows so that system performance can be controlled and optimized in real time. Therefore, in this project, we successfully developed AI-based signal coordination and control strategy for optimized traffic mobility along Nimitz highway and Ala Moana Boulevard in Honolulu, Hawaii. Figure I.3.3.1 demonstrates the AI-based modeling and control system architecture and implementation to optimally coordinate signal controls for the system. The advantage of using AI-based models is that these models can be adaptively learned using evolving real-time data. Once a reliable system model is obtained, the control design using AI-based control is required so that an AI-based real-time closed-loop feedback control can be established that uses the traffic flow state as a feedback information to control the signal timing intelligently at intersections so that the resulting traffic flow can be made smoother with minimized energy consumption. This control requires controller design using AI techniques. Because of the random nature of the traffic flow systems, stochastic optimal control in a multi-objective Bayesian framework will be investigated.

b) Major R&D Challenges: In parallel with artificial neural network and AI development since 1958, significant research on AI modeling and controls for networked traffic system are reported in the literature. Most studies only consider a few intersections, and large-scale field testing has not been reported because of the lack of comprehensive real-time data and user-friendly interfaces to the implementation [5] – [8]. Moreover, energy efficiency has not been well addressed. This constitutes the following challenges and technical barriers:

a. Although the theory of AI-based modeling and control for signal control is maturing, the field testing and closed-loop control implementation for large number of intersections is still limited because of the insufficient real-time data for fast feedback control realization;

b. The existing AI-based modeling for transportation systems cannot yet capture the nonlinear and dynamic stochastic nature with high reliability and robustness; and

c. Guaranteed control performance for the energy minimization is still lacking.

Research that addresses the above problems—in particular, the real-world implementation for AI-based approaches—is needed to demonstrate their true effects rather than simply performing simulations. This demonstration constitutes the primary objective of the proposed research, in which applying AI-based signal coordination and controls for enhanced mobility with energy efficiency will be carried out for the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu following the recent major investment ($6 million) on signal infrastructure and data acquisition platform by the State of Hawaii and DOT.

c) Significant Research Achievements: The project brings together expertise of DOE's ORNL on AI–based modeling and control, the University of Hawaii (UH) on networked intersectional modeling, and Econolite Systems on signal infrastructure hardware and controls to apply AI-based modeling and signal coordination controls (Figure I.3.3.1) for the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu, Hawaii. The major research achievements include the following aspects:

a. Successfully establishing nonlinear dynamic stochastic models that reflect the real-world traffic flows and energy consumption using AI techniques and deep learning approaches;

b. Effectively developing optimal AI control for the traffic flow system with minimized energy usage for the 34 intersections in the arterial system shown in Figure I.3.3-1, leading to the real-time AI-based closed-loop coordinated signal control in Figure I.3.3.1; and

c. Successfully conducting on-site testing and validation for the modeling and control algorithm in (a) and (b).

Objectives

The major objectives of this project include

a. Apply and evaluate an AI-based traffic control system enabled by cutting-edge sensing technologies and intelligent control and optimization to enhance mobility performance and minimize energy consumption along a major arterial in Honolulu—the Nimitz Highway and Ala Moana Blvd segments. This arterial is about 5.25 miles long and runs predominantly north and south with 34 signalized intersections.

b. Use the real-time data in Econolite System to build up multi-input and multi-output (MIMO) AI-based data-driven models using an artificial neural network.

c. Develop AI-enabled signal coordination controls that can optimally manipulate the signal timing of the 34 intersections along the arterial.

d. Use the signal control and traffic flow real-time platform provided by UH and Econolite to implement, test, and validate the AI-based modeling and control algorithms in terms of AI impact on efficiency of mobility.

Approach

UH and Econolite have updated and installed innovative control system hardware along the Nimitz Highway and Ala Moana Boulevard arterial with the latest integrated traffic control and management technologies to improve traffic safety and mobility performance for all the travel modes. Using the above data platform and the hardware infrastructure, the project has been executed with the following logical approaches:

a) Baseline performance of system: The current Econolite system displays the pretimed and actuated coordinated signal controls. This has been used as a baseline case for comparison.

b) AI-based modeling: Because the traffic demand and traffic flows (number of vehicles and their compositions) are random, the system is both stochastic and MIMO. A MIMO dynamic model has been established that characterizes the relationship between these inputs and outputs. Using neural network modeling [9] to obtain reliable and robust AI-based models for the traffic flow system.

c) AI-based closed-loop control design: Following the establishment of reliable and robust AI-based dynamic models, the MIMO AI-based controller design has been carried out so as to reduce travel delays of the 34 intersections in a closed-loop feedback fashion with minimized energy consumption [10].

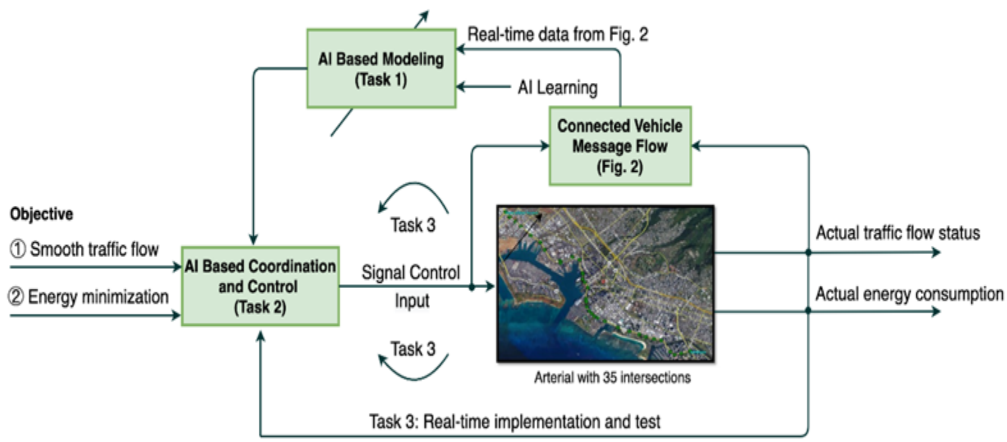


Figure I.3.3.1 The proposed real-world implementation using AI techniques

d) Real-world testing and implementation: After the modeling and control were obtained and validated, real-time implementation has been carried out for the closed-loop system in Figure I.3.3.1. This work consisted of establishing the interface with the Econolite information system and conducting comprehensive testing scenarios to show the benefits of AI-based controls for improved mobility with reduced energy consumption.

Results

a) Hybrid Neural Network Development

The hybrid neural network (HNN) model in Equation (1) was developed for predicting one step ahead delay across the entire arterial.

$$y(k+1) = Ay(k) + Bu(k) + F(y(k), u(k-1), v(k)\,;\,\pi) \tag{1}$$

where, Matrices A and B are parameters for the linear part of the system and F(.) is a neural network representing and approximating the nonlinear dynamics of the system. The closed loop adaptive signal control optimization problem was formulated to obtain the optimal set of green light duration for each cycle as given below:

$$\begin{gathered} min||w \cdot y(k+1)||^2 \\ s.t. u_{min} \le u(k) \le u_{max} \end{gathered} \tag{2}$$

where w is the weighting factor, u_{min} and u_{max} are the constraints of green light duration based on cycle length and ring barrier configurations of each phase and intersection. The following iterative procedure is used to adaptively update the weights of the model in (1) using the data generated from VISSIM simulation by controlling the green light duration for each cycle. As VISSIM is calibrated using Econolite System data, the closed loop control can reliably simulate the actual implementation effect.

b) **Developing Weighted Probability Density Function (PDF) Shaping for HNN Models**

The objective of the modeling is to select the tuning or training of model parameters (such as neural network weights) so that the modeling error distribution is made as close as possible to a narrowly distributed Gaussian centered at zero mean value. This is a probability density function control problem, and the theory is to train the matrices and the weights so that the modeling error PDF is made to follow an impulse PDF centered at zero as close as possible. Therefore, we developed and tested a novel and promising PDF shaping model to train neural networks. The goal of the proposed PDF model is to shape the distribution of modeling errors, which are the discrepancies between the predicted outputs of the neural network and the actual target values. Instead of minimizing the sum of squared errors as in traditional methods, this approach aims to make the modeling error distribution as close as possible to a narrowly distributed Gaussian centered at zero mean value. This can potentially lead to more robust, reliable, and generalizable models for network control applications. The overall structure of the modeling error PDF shaping based training and learning is shown in Figure I.3.3.2.

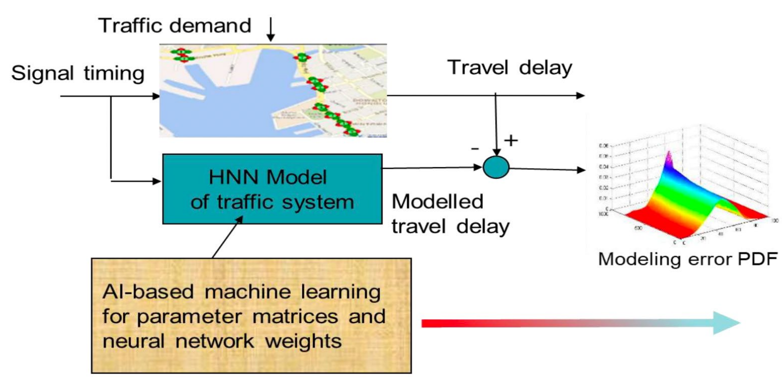


Figure I.3.3.2. The PDF shaping based learning of the system dynamics

In particular, we tested three loss functions in neural network training with real-world data in Corridor 2 with 7 intersections. Eq. (3) aims to shape the modeling error distribution $\gamma_e(x,\theta)$ as close as possible to a narrowly distributed Gaussian$g(x)$, which is a pre-specified narrowly distributed Gaussian PDF close to an impulse function.

$$\min_{\theta} J = \int_{-\infty}^{+\infty} \sigma(x)[g(x) - \gamma_e(x,\theta)]^2 dx, \tag{3}$$

In Eq. (4), we can also use the following Kullback-Leiber distance to measure the difference (i.e., the distance) between the target and the modeling error PDFs.

$$\min_{\theta} J(\theta) = \int_{-\infty}^{+\infty} \sigma(x)\gamma_e(x,\theta)\log\left[\frac{\gamma_e(x,\theta)}{g(x)}\right]dx \tag{4}$$

In Eq. 5), entropy performance function is used to minimize the uncertainties embedded in the modeling error.

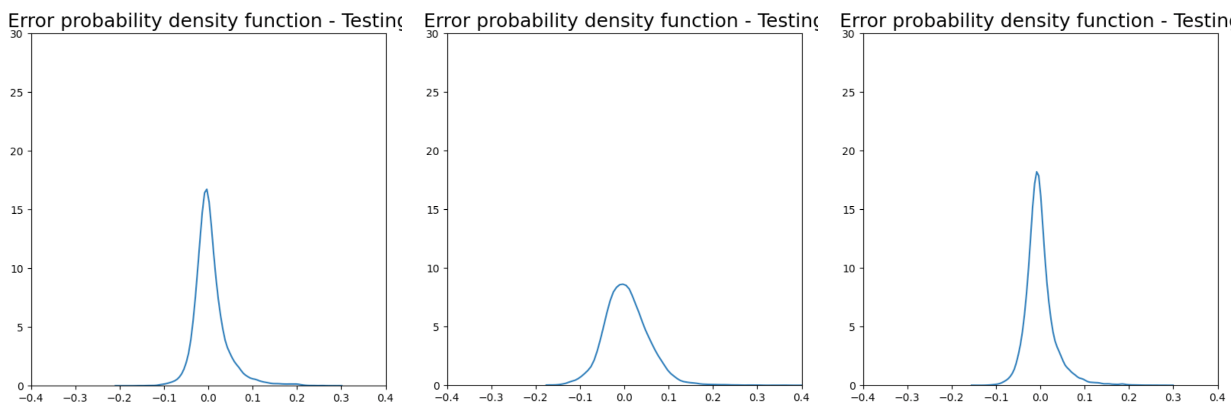
$$\min_{\theta} J(\theta) = -\int_{-\infty}^{+\infty} \gamma_e(x,\theta) log(\gamma_e(x,\theta))dx + \ mean \tag{5}$$

Table I.3.3.1 presents the prediction results of the hybrid neural network model with three different loss functions. Among the evaluated loss functions, the one based on Entropy (Eq. 5) stands out as the best performer, achieving the lowest mean absolute percentage error (MAPE) at an impressive 7.03%. In addition, the table also demonstrates that the PDF loss function performs well, achieving a MAPE of 8.03%. This result indicates that the Entropy-based and PDF loss functions capacity to address uncertainty and emphasize the importance of modeling errors as a probability distribution. This approach allows the neural network to better capture the varying levels of uncertainty in different predictions, leading to improved overall accuracy and robustness.

Table I.3.3.1 Prediction results with different loss functions

Intersection	10	11	12	13	14	15	16	Average
PDF (Eq. 1)	8.62%	8.03%	10.91%	9.19%	5.30%	5.20%	6.22%	**8.03%**
KL distance (Eq. 2)	16.14%	9.74%	10.54%	15.85%	9.17%	14.92%	9.99%	**11.99%**
Entropy (Eq. 3)	8.67%	6.95%	6.63%	8.74%	5.19%	7.56%	8.91%	**7.03%**

Figure I.3.3.3 the probability density function of modeling errors for the testing data using three distinct loss functions. Upon observation, it becomes apparent that both the PDF and entropy-based loss functions exhibit narrower and taller probability density distributions in comparison to the KL distance. The narrower and taller nature of the PDF and entropy-based loss functions' distributions signifies that the modeling errors are more concentrated and centered around zero, indicating a superior alignment between the predicted values and the actual target values. This closer fit to zero implies that the predictions made by the model are more accurate and exhibit reduced variability, leading to better overall performance in capturing the underlying patterns in the data.



(a) PDF (b) KL distance (c) Entropy

Figure I.3.3.3 Probability density distribution of modeling error

c) HNN Model Calibration and Simulation Data Integration

The AI-based adaptive signal control algorithm has been implemented in VISSIM for PM peak hour simulation. The HNN model has been trained using field data from 4 pm–7 pm for the month of March 2021 to May 2021 and has been validated using data from June 2021. The model and control have already shown great potentials on delay reductions. In order to further improve the model to capture all the variations in the field and prepare for 24x7 field implementation, the model is trained with additional data points. Field data from 5 am to 7 pm of March 2021 to May 2021 have been used for training and 5 am to 7 pm of June 2021 data have been used for validation. The model training process is essentially solving an optimization problem to find the best model parameters, i.e., A, B, π matrices that minimize the error (E) as given in Eq. (6) and (7).

$$\min_{A,B,\pi} E = \frac{1}{2}(\hat{y}(k+1) - y(k+1))^2 \tag{6}$$

$$\hat{y}(k+1) = A\hat{y}(k) + Bu(k) + f(\hat{y}(k), u(k-1), v(k), \pi) \quad (7)$$

The function $f(y(k), u(k-1), v(k)$ is modeled using neural network and the matrices A, B, π are trained using gradient based approach.

The total number of data points being considered is 11,141 (March 1, 2021 to June 30, 2021) – 5 am to 7 pm, with 80% (March-May) split into training set and 20% (June) split into validation. The full daytime data covers wider range of traffic conditions and additional handling on the raw data is needed. The standard 1.5 IQR (interquantile range) rule was used as a threshold to determine outliers. This means that the data points below (Q1 – 1.5*IQR) and the data points above (Q3 + 1.5*IQR) were considered to be outliers. Figure I.3.3.4 illustrates the data outlier distribution at various intersections along the arterials. The threshold for Q1 and Q3 were taken to be ±5% rather than ±25% of the data points to avoid leaving useful information from the dataset.

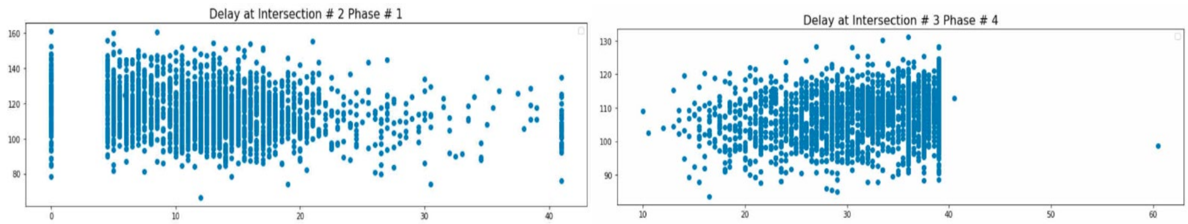


Figure I.3.3.4 Outliers at various intersections

Table I.3.3.2: Intersection level MAPE for Corridor #1 as An Example.

Intersection	HNN Model Error (%)
1	3.93
2	4.34
3	4.17
4	4.11
5	4.68
6	4.87
7	4.83
8	5.01
9	3.73

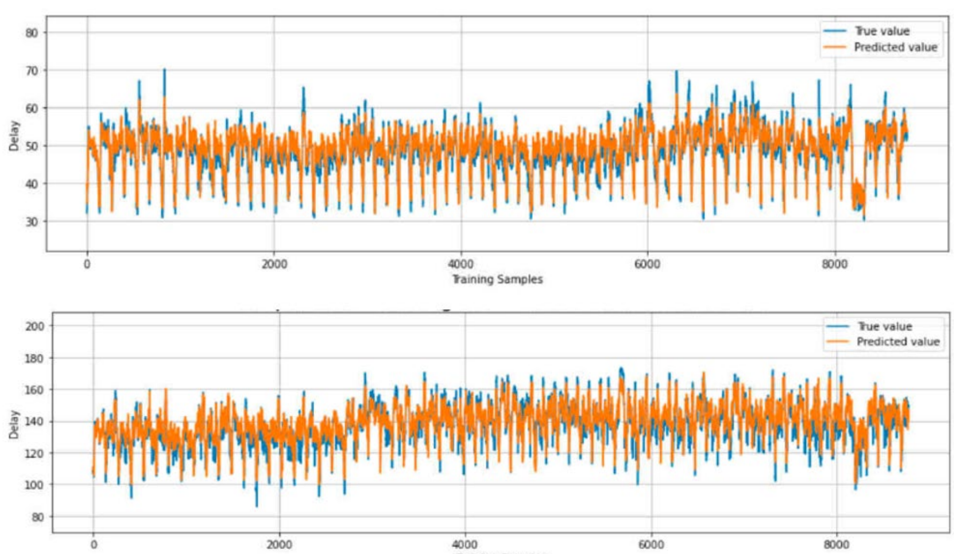


Figure I.3.3.5 Comparison of HNN model performance and the actual data

Once the outliers have been detected, they cannot be simply removed since the continuity of the time series will be broken. Hence, k-nearest neighbors imputation method was used to replace the outliers and missing data points. In this approach, the Euclidean distance from the missing data point is calculated from the remaining data points. Then, the k-nearest neighbors of the missing data point are determined. The mean value of the nearest neighbors will be taken as the value of the outlier and missing data point. In our approach, the value of 'k' is taken to be 5. Once the dataset is prepared, the model training has been performed as usual with MAPE being the loss metric. The results of the model performance for each intersection in Corridor #1 is tabulated in Table I.3.3.3. The MAPE for all the intersections is within 10% of the threshold and can be confirmed by observing the comparison of individual phases performance from the baseline as shown in Figure I.3.3.5.

In order to fully implement the AI based control strategy 24/7, the additional dataset was collected for the months of July 2021–February 2022. Hence, the total number of available datapoints have been increased by 10 folds to account for more variations during different times of the day. The HNN model has been re-trained without modifying the neural network architecture and the MAE results have been summarized for corridor #1 (intersections 1-9) in Table I.3.3.3. The plot of actual values versus predicted values for some of the intersections is also provided in Figure I.3.3.6. It can be observed that the model was able to predict the variations for most part of the intersections but missed out some of the extreme values in the dataset. In order to improve the results, the HNN model with PDF shaping is used for the loss function to improve the results further.

Table I.3.3.3: Mean Absolute Error (MAE) for intersections in Corridor #1

Intersection	Training MAE (s)	Testing MAE (s)
1	11.3	9.5
2	15.5	13.9
3	16.5	15.3
4	18.1	17.5
5	23.1	24.8
6	20.4	20.4
7	18.9	17.2
8	11.3	9.7
9	7	5.1

Figure I.3.3.6 : Comparison of actual versus predicted values for some intersections in Corridor #1

d) Energy Evaluation Model Improvement

The objective of energy modeling is to reveal the relationship between the signal timing plans *u(t)* in Equation (1) and the energy consumed when the durational traffic volume is given. This is a challenging modeling issue where we need to map the time series functions (signal timing plan) with a crispy value (energy) at the end of concerned time duration.

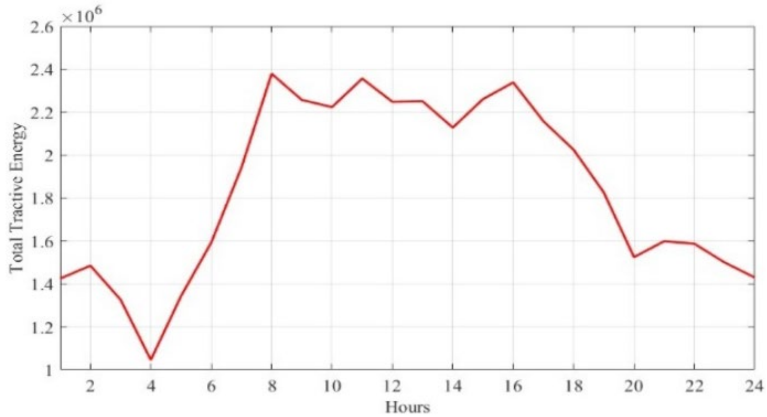
1. Data Preparation

The signal timing plan for every intersection consists of three to six phases, which adds up to a total of 43 phases for this corridor. The mean and variance of green duration time in each phase are aggregated at the hourly level as the dependent variable for the neural network model. Therefore, there are a total of 86 dependent variables in the energy model. Table I.3.3.4 presents the descriptive statistics of dependent variables for the first intersection of the corridor. In the table, the variable 'Mean of Green-N1-P1' represents the mean value of the green duration of Phase 1 at the first intersection. Phase 2 and Phase 6 serve as major approaches with a long green duration.

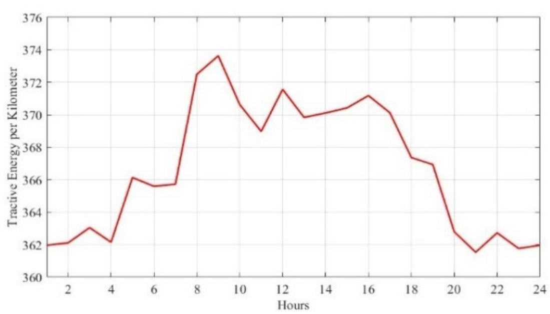
Table I.3.3.4 Statistics of dependent variables for the first intersection of the corridor

Variables for the first intersection	Statistics based on one hour time span			
	Mean (s)	SD (s)	Min value (s)	Max value (s)
Mean of Green-N1-P1	18.19	1.59	12	20
Variance of Green-N1-P1	13.62	9.56	0	27.78
Mean of Green-N1-P2	150.84	1.82	146.6	157
Variance of Green-N1-P2	20.54	13.66	0	56.67
Mean of Green-N1-P3	10.97	0.82	10	13.5
Variance of Green-N1-P3	3.56	2.47	0	6.94
Mean of Green-N1-P4	169.03	0.82	166.5	170
Variance of Green-N1-P4	3.56	2.47	0	6.94

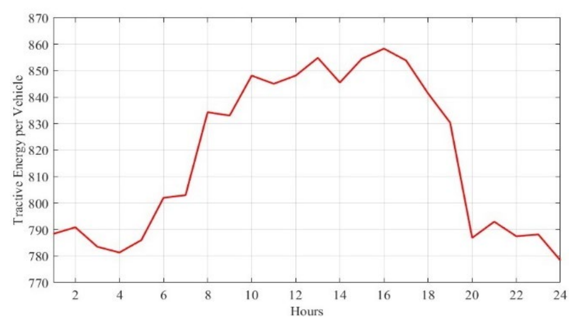
In terms of the system-level energy consumption variables, the total tractive energy consumption, the tractive energy consumption per kilometer, and the tractive energy consumption per vehicle are estimated for all the vehicles in the network at every hour, which is consistent with dependent variables. Figure I.3.3.7 shows the variation of three energy consumption features over one day. It is clear to see that the energy consumption overnight is significantly lower than during the daytime due to less delay and congestion. The peak hour of energy consumption per kilometer is 8:00-10:00 and the peak hour of energy consumption per vehicle is 15:00-17:00. These three energy consumption features are used as the dependent variables for three ANN models, respectively. The VISSIM simulation generated a total of 403 hours of data. The dataset is split into 75% training dataset and 25% test dataset. The training dataset was used for the model calibration, and the test dataset was used for the model validation and prediction. A process of normalization is applied to both datasets.



a. Total tractive energy



b. Tractive energy per kilometer



c. Tractive energy per vehicle

Figure I.3.3.7 Variation of three energy consumption features over one day

2. Intersection-Level Energy Modeling

For intersection-level energy modeling, the data preparation process is quite different from the previous corridor-level energy modeling. Every sample of modeling data is collected for one intersection at every signal cycle. Figure I.3.3.8 shows the data preparation flowchart for intersection-level energy modeling. In addition to the signal timing variables, we also introduced traffic flow-related variables, including traffic volume, travel time, and delay. The simulation time period has also been expanded to 24 hours per day (four different signal timing patterns) rather than only focusing on the afternoon peak hour, which can provide more variance in the data and potentially improve the model performance.

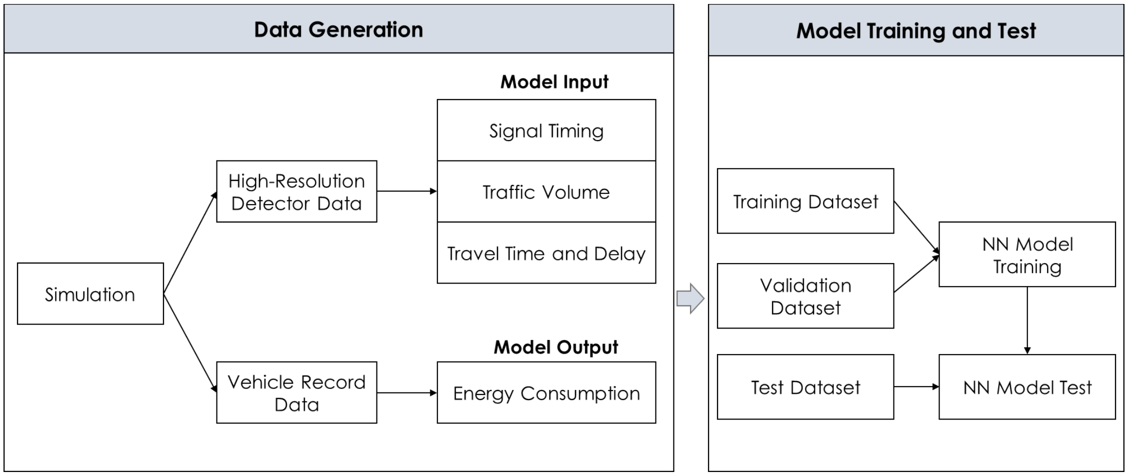


Figure I.3.3.8 Data preparation flowchart for intersection-level energy consumption modeling

3. Result Analysis

Three baselines are also developed to compare the performance of model calibration and model prediction with the proposed mode: 1) LR, a linear regression model. 2) ANN-MSE, an artificial neural network model using MSE as the loss function. 3) ANN-PDF control, the proposed model that applied PDF control theory to build the loss function. Furthermore, an importance analysis was conducted to extract significant variables in the ANN model. The specific results and analysis are shown as follows.

3.1. Evaluation of Prediction Performances

The same four metrics are also adopted to evaluate the prediction performances by using the test dataset. The prediction results of models for three energy consumption features are shown in Table I.3.3.5 to Table I.3.3.7. The ANN-PDF control shows the best prediction result than other baselines, and the prediction performance of the total tractive energy model is better than the other two energy consumption features.

Table I.3.3.5. Prediction Performance for Total Tractive Energy

Method	Performance measure			
	R^2	RMSE	MAE	ISD
LR	0.556	0.121	0.096	0.302
ANN-MSE	0.639	0.109	0.087	0.24
ANN-PDF control	0.687	0.102	0.085	0.225

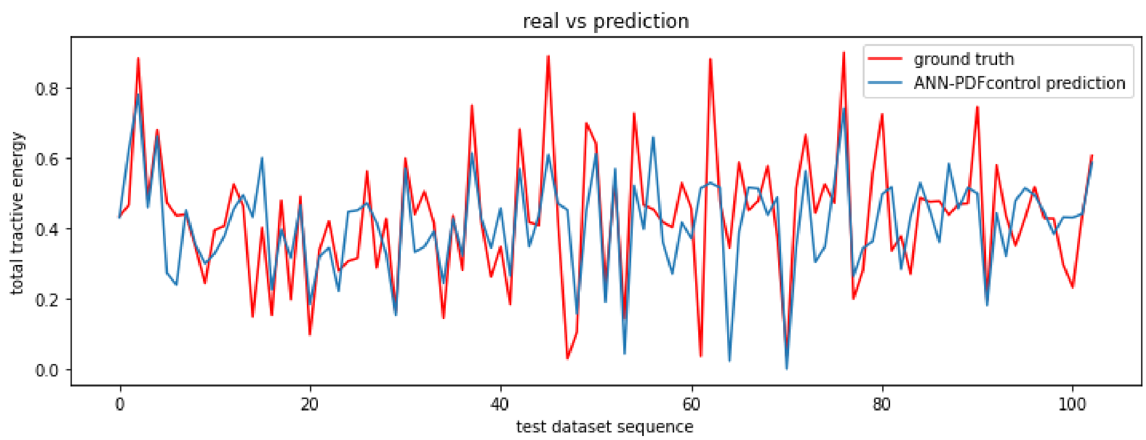
Table I.3.3.6. Prediction Performance for Tractive Energy per Kilometer

Method	Performance measure			
	R^2	RMSE	MAE	ISD
LR	0.373	0.123	0.1	0.274
ANN-MSE	0.436	0.117	0.093	0.2
ANN-PDF control	0.527	0.107	0.081	0.177

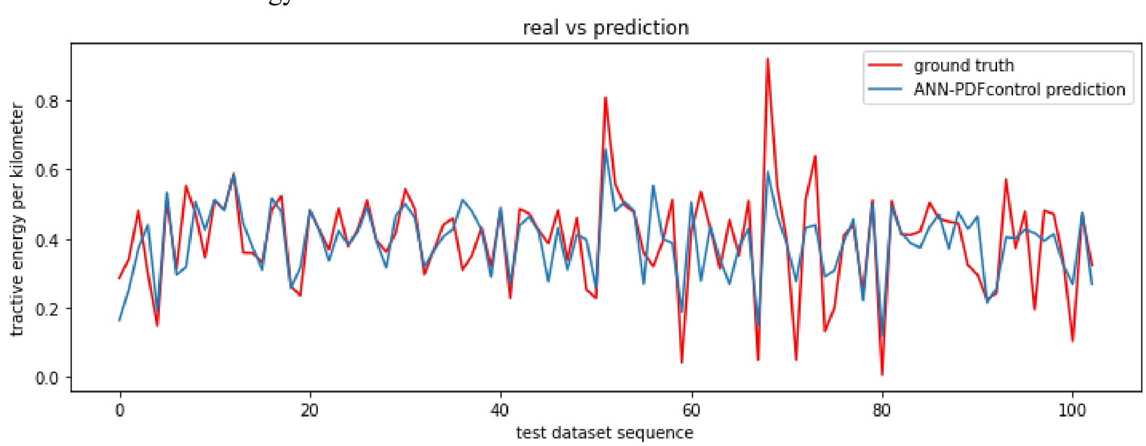
Table I.3.3.7. Prediction Performance for Tractive Energy per Vehicle

Method	Performance measure			
	R^2	RMSE	MAE	ISD
LR	0.396	0.151	0.121	0.294
ANN-MSE	0.461	0.148	0.117	0.243
ANN-PDF control	0.502	0.142	0.112	0.231

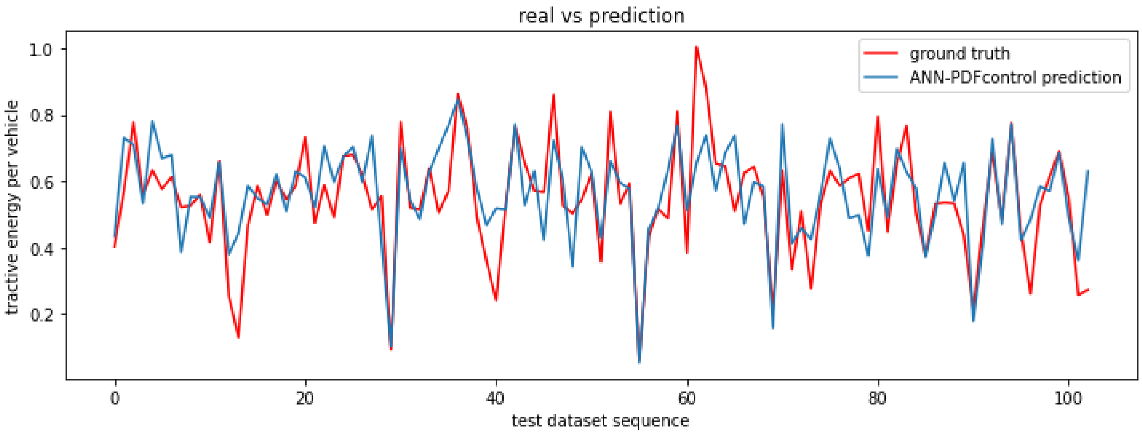
Figure I.3.3.9 the comparations between the ground truth and predicted results from the ANN-PDF control model. In this figure, the shapes of the predicted line are quite close to the ground truth for three energy features, which verified the effectiveness of the proposed model for energy consumption prediction using signal timing parameters.



a. Total tractive energy



b. Tractive energy per kilometer



c. Tractive energy per vehicle

Figure I.3.3.9 Real vs. prediction for three energy consumption features

3.2. Permutation Importance (PI) Analysis

A Permutation Importance (PI) method is applied to analyze the impact of the signal timing parameters on the prediction of energy consumption. The principle behind the PI analysis is quite straightforward: if we randomly shuffle a single feature in the dataset while leaving the target variable and all other features in place, how would that affect the final prediction performances? According to this principle, the PI can be formulated as follows:

$$PI = \frac{\quad}{F} \times 100\% \qquad (8)$$

where F indictes the prediction result of the model before permutation, F^{-} is the prediction result of the model after permutation. In this case, we use MAE to represent the prediction result. The larger value of PI represents the corresponding variables' larger impact on the energy prediction. Take the total energy consumption as an example, Figure I.3.3.10 and Figure I.3.3.11 show the PI values for the 43 variables related to the mean of green duration and 43 variables related to the variance of green duration. We have repetitively calculated the PI value ten times for each variable. The gray lines in the figures represent the results for the ten calculations, and the red lines represent the average value of PI. In terms of the impact of the mean of green duration, phase 30 is the most important phase, which corresponds to Phase 2 (i.e., eastbound through) of intersection No. 6. This implies that the duration of the eastbound through phase at intersection No. 6 has the highest impact on the total energy consumption. The PI values of the variance of green duration reveal that phase 4, corresponds to Phase 6 (i.e., westbound through) at intersection No. 1, is the most important variable. This finding implies that the variation of the westbound through phase at intersection No. 1 has the highest impact on the total energy consumption.

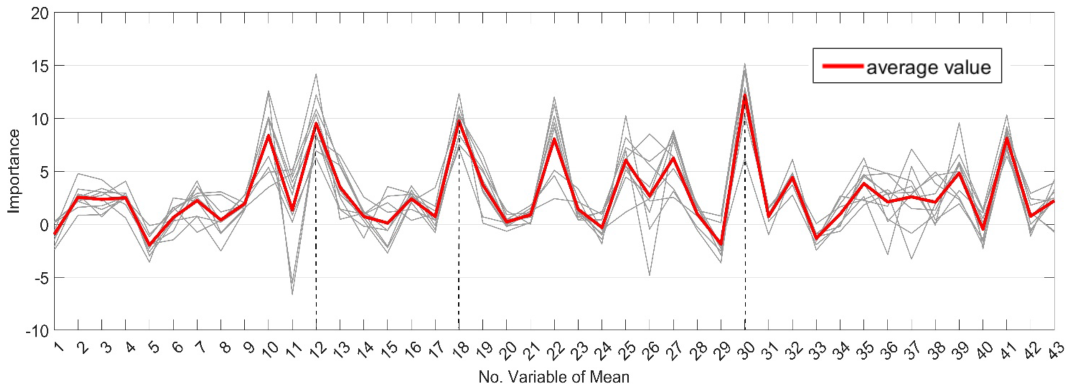


Figure I.3.3.10. The importance of the 43 variables related to the mean of green duration to the total energy consumption.

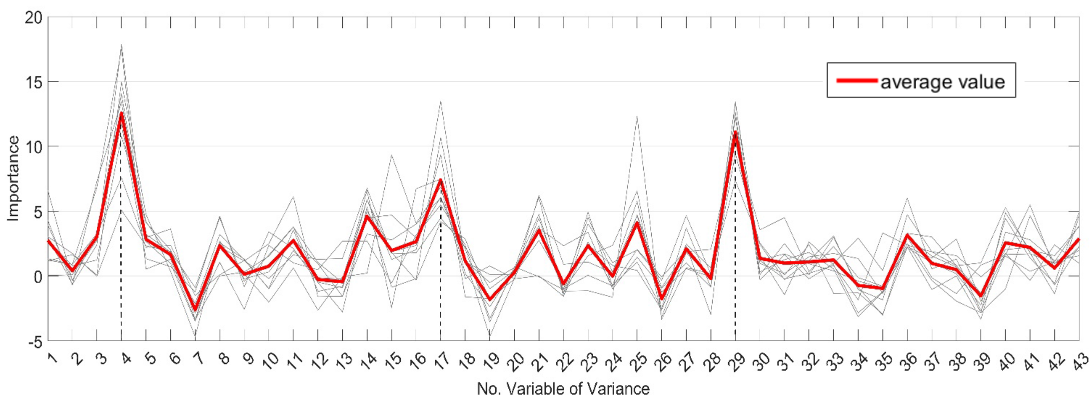


Figure I.3.3.11. The importance of the 43 variables related to the variance of green duration to the total energy consumption.

e) Real-world Implementation and Experimental Tests

Starting in January 2023, the research team conducted real-world testing of the control implementation workflow design as shown in Figure I.3.3.12, which depicts the current workflow for the real-time signal control testing and implementation. In the *Physical System*, high resolution data are collected from field signal controllers and stored to a SQL database. The *Data Broker* queries the high-resolution data, which are processed by the *Data Processor* to derive inputs for the *Control Optimizer*. The *Control Optimizer* then determines the optimal timings for the next control cycle based on the inputs (e.g., delay and volume). The optimal signal timings are then sent as NTCIP commands back to the *Physical System* through the *Data Broker*, and the new optimal timings are then being implemented. Note that in the current setup, as a testing and verification step, these NTCIP commands are sent to the signal controller in the lab cabinet instead of the field controllers. Once the laboratory testing and validation are completed, field implementation will be conducted and the NTCIP commands will then be sent directly to field signal controllers.

Between January and September, the research team conducted multiple rounds of testing that started from online in-lab testing to off-hour short-duration online closed-loop field testing to verify the workflow design and execution. After the workflow was tested and verified, we further conducted two weeks of online closed-loop control and tastings. As shown in Figure I.3.3.13, the first week of online-testing was conducted from 12:00 AM to 5:00 AM every day from March 30 to April 5, 2023 at two intersections (#1 area) of the study area; and the second week of online-testing was 24/7 continuous testing conducted from April 20 to April 27, 2023 at the seven intersections (#2 area) of the second corridor. Figure I.3.3.14 illustrates the control parameters settings and manual observations conducted by the ORNL researchers and traffic engineers during the field testing at two intersections.

Furthermore, the system hardware structure with a new wall-panel screen was established in May 2023 and the whole hardware structure is shown in Figure I.3.3.15. The front panel of the tests is shown in Figure I.3.3.16, where it can be seen that the traffic flow and signal infrastructure are given together with a multiple moving circle that shows the real-time signal splits over a selected intersection per based upon the Econolite Systems platform. Figure I.3.3.17 illustrates the responses of the typical signal splits of an intersection where the solid lines are the optimal solution, and the dotted lines give the actual applied green timing after the possible activation of pedestrians crossing.

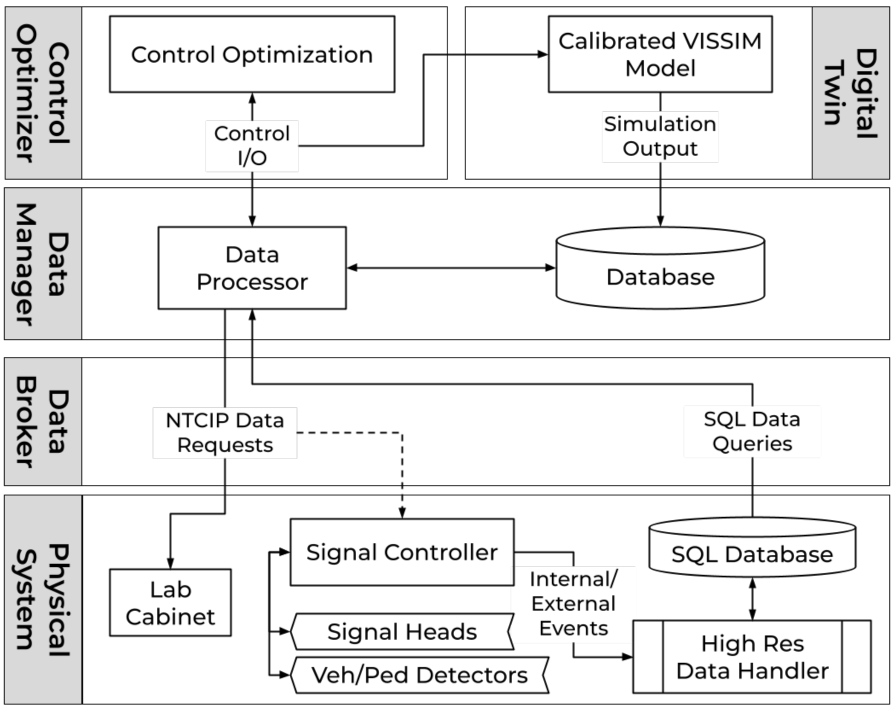


Figure I.3.3.12 Real-time signal control implementation and testing workflow

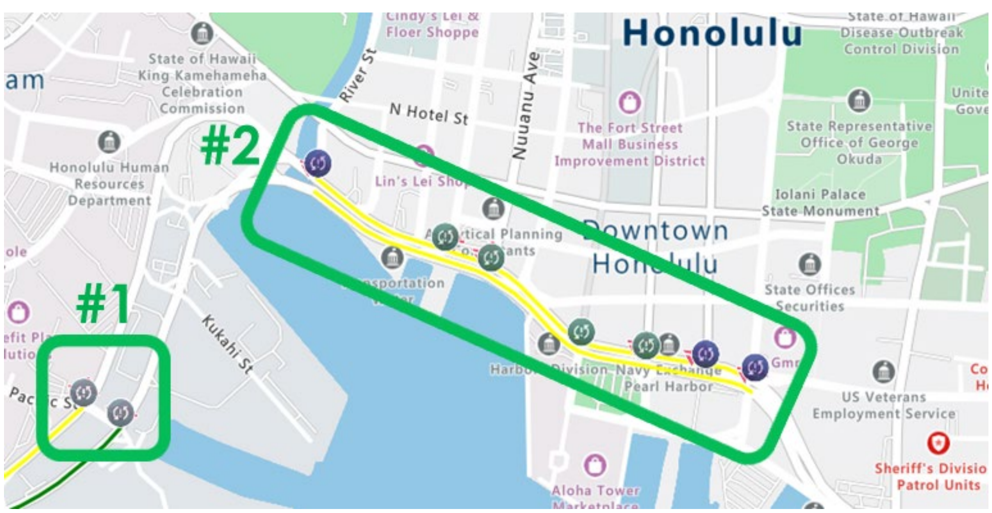


Figure I.3.3.13 Field implementation – online testing locations in April 2023

Figure I.3.3.14 Online testing – field observation in April 2023

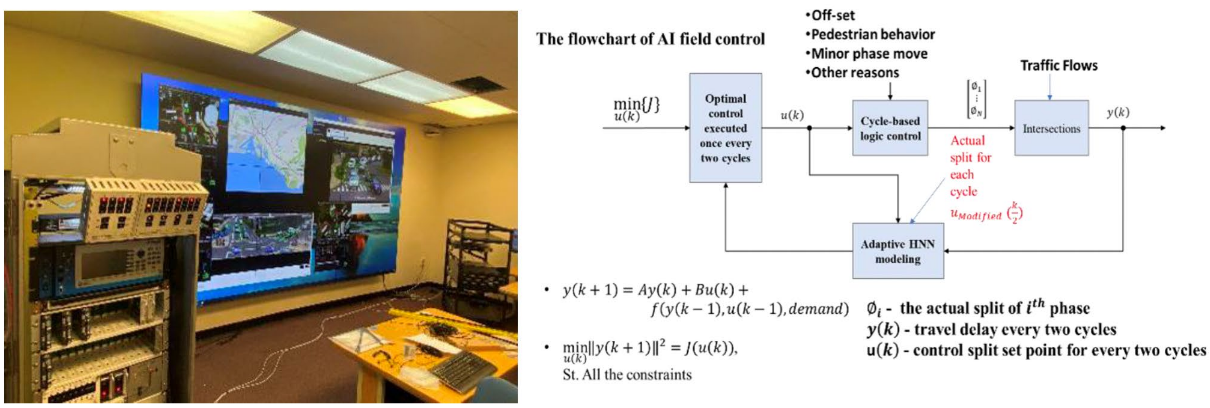


Figure I.3.3.15 The hardware structure of 24/7 implementation

Figure I.3.3.16 The demonstration panel and interfaces

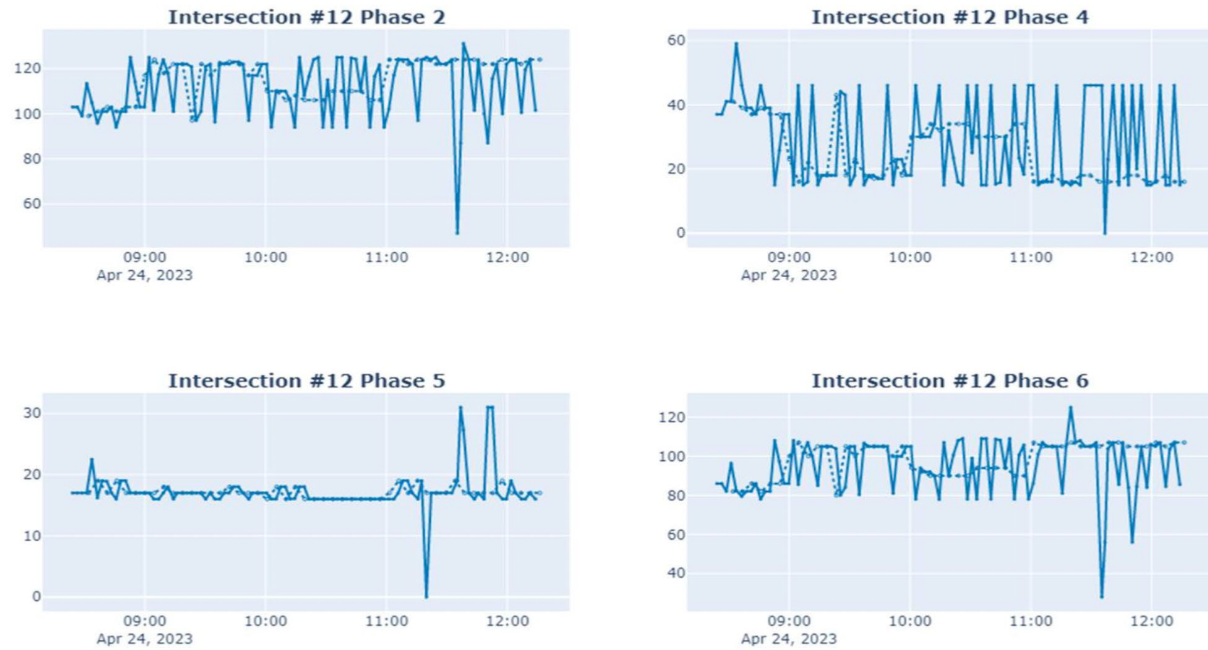


Figure I.3.3.17 The green timing of a typical phase showing the optimal/applied timing duration

Quantitative testing results of the 24/7 continuous AI-based signal control testing was compared with the week immediately after (April 27 to May 4) that was controlled by baseline strategy. The comparison, in terms of delay per vehicle by intersection and phase, is shown in Table I.3.3.8 and Figure I.3.3.18. As shown in Table I.3.3.8, the weighted delay of the adaptive control was on average 9% lower than that of the baseline control, with a maximum delay reduction up to 27% at the intersection level. This comparison has verified that the implemented AI-based adaptive control was effective. Figure I.3.3.18 shows detailed delay comparison by each intersection and phase, and it shows that for majority of the phases, the adaptive control method reduced the overall delay. It is also noted that for some phases (e.g., Phase 5 of Intersection 11), the adaptive control increased the delay. These specific intersections and phases where delay got worse are continued to be investigated and will potentially be used to further improve the adaptive control algorithm when reasonable. Compared with baseline period (February 16–23, 2023), the AI based control shows ~10% average delay reduction and less variation.

Table I.3.3.8. Average delays comparison between baseline semi-actuated control and adaptive control

Control	Unweighted Delay (s)	Weighted Delay (s)
Baseline	76.8	61.6
Adaptive	73.7	56.0

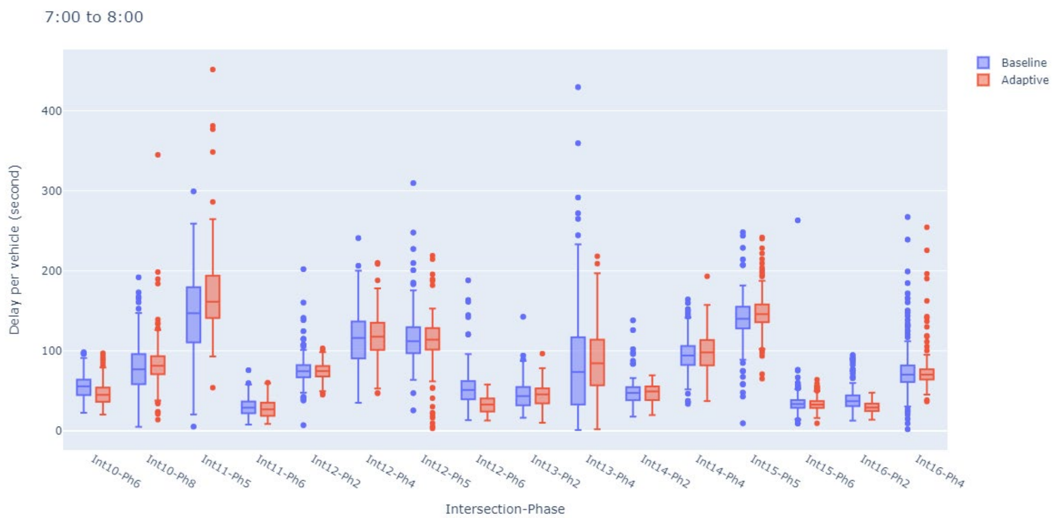


Figure I.3.3.18 Intersection and phase-based comparison of delay per vehicle between baseline (original timing pan and control strategy) and the implemented adaptive control

In August and September 2023, the research team further conducted another set of experiments to extend our April experiments from Corridor 2 to Corridors 1, 2, and 3, with a total of 24 intersections as shown in Figure I.3.3.19. The experimental tests were conducted under various traffic conditions during multiple days. We have been in the process of analyzing the field data and comparing the signal control system performance based on the baseline scenarios under similar traffic patterns. Our preliminary analysis results indicate the proposed AI-based control optimization method has consistently outperformed the existing control coordination plans under prevailing traffic conditions. Figure I.3.3.20 shows the consistent improvements achieved by the proposed AI-based control method along Corridor 1, 2, and 3 from 8:00 to 20:00 on one day. Table I.3.3.9 shows the quantitative control delays and the corresponding improvement comparisons. In-depth analyses have been conducted to further elaborate their performance for improvement purposes. We plan to conduct the signal control performance tests along Corridor 4 in November and December 2023 to further consolidate the entire arterial testing study under prevailing traffic conditions.

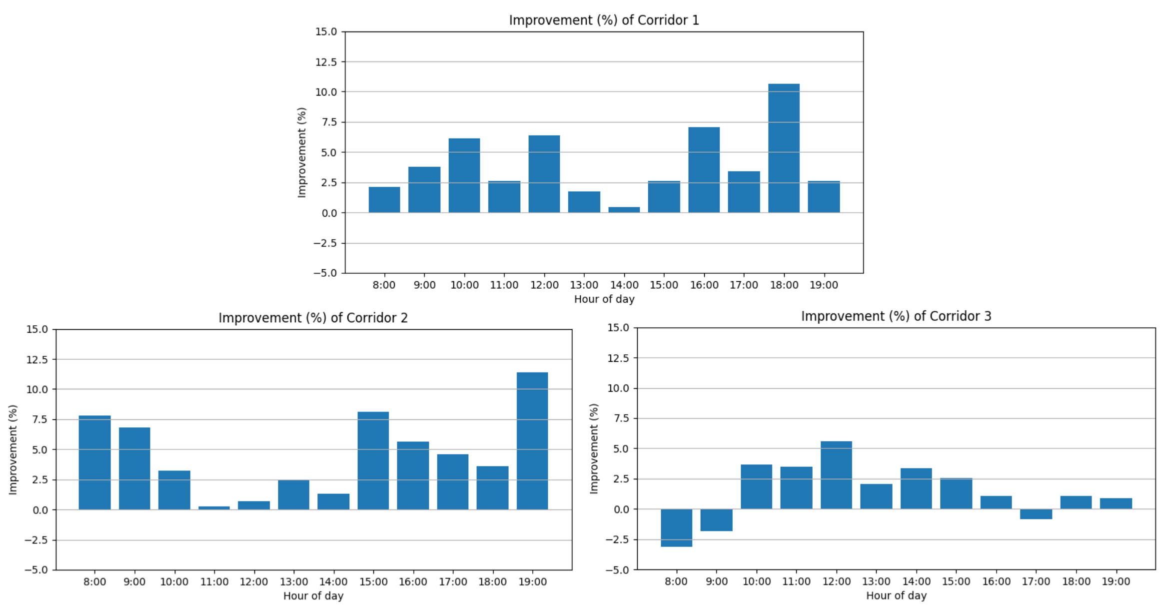


Figure I.3.3.19 Locations of the August and September experiments: a total of 24 intersections along Corridors 1, 2, and 3 on Nimitz Highway and Ala Moana Boulevard

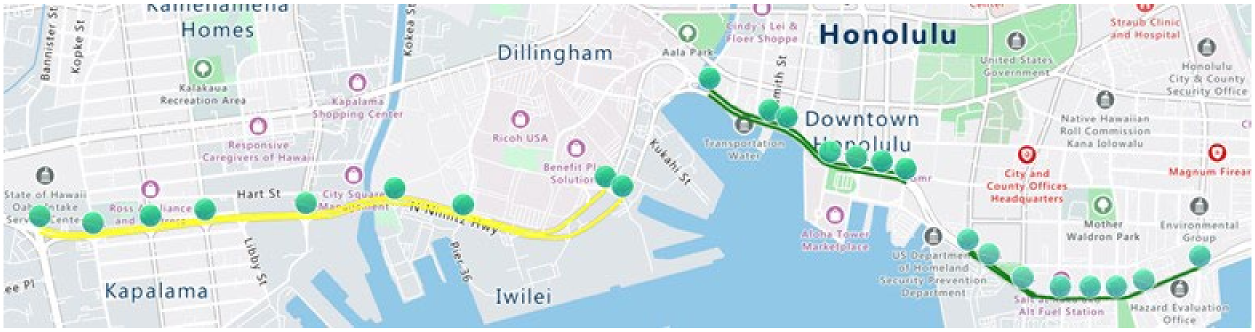


Figure I.3.3.20 The improvement in Corridor 1, 2, and 3 from 8:00 to 20:00 on one day

Table I.3.3.9. The comparisons of delay per vehicle for baseline system and adaptive system

	Delay per vehicle (s) of baseline system	Delay per vehicle (s) of adaptive system	Improvement (%)
Corridor 1	50.35	48.25	4.12
Corridor 2	54.02	51.50	4.63
Corridor 3	48.85	47.24	3.30

Conclusions

FY 2023 has been a year of success, and the team has completed all the planned milestones. To summarize, the accomplishments are given in the following:

- Established nonlinear dynamic stochastic models that reflect the real-world traffic flows and energy consumption using AI techniques and deep learning approaches.
- Completed the VISSIM simulation development and completed optimal and adaptive controller design.
- Completed the AI neural network training and validation and implemented all the AI-based signal control tasks.
- Complete the implementation of the 24/7 real-time control along Corridors 1, 2, and 3.
- Successfully submitted the patent application.
- Gave two keynote talks at international conferences (Spain and Japan).
- Gave demonstrations at the WASHTO conference in Hawaii, June 2023.

Key Publications

1. Subramaniyan, Arun; Wang, Chieh; Shao, Yunli; Li , Wan ; Wang, Hong; Zhang, Guohui; Ma, Tianwei. Hybrid Recurrent Neural Network Modeling for Traffic Delay Prediction at Signalized Intersections Along an Urban Arterial. IEEE Transactions on Intelligent Transportation Systems. Vol. 24, No. 1. 2022. pp. 1384-1394.

2. H Wang, Optimal and Secured Control using V2V Information: from Powertrain to Multiple Autonomous Vehicles, The Twelfth International Conference on Advances in Vehicular Systems, Technologies and Applications, VEHICULAR 2023, March 13, 2023 to March 17, 2023 - Barcelona, Spain (**Keynote Talk**)

3. H Wang, Intelligent Transportation Systems via V2V Information: Integration of Vehicle (Powertrain), Signal control and Adaptive Routing, ITET & ISDEA **Keynote Presentation**, Japan, May, 2023

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10. H Wang, S Patil, HM Abdul Husian and S Young, Stochastic distribution modeling and control for traffic flow at signalized intersections, *IEEE Transactions on Intelligent Transportation Systems*, 2020.

Acknowledgements

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I.4 Advancing Driving Automation through Connectivity

I.4.1 A Cooperative Driving Automation (CDA) Framework for Developing Communication Requirements of Energy Centric CDA Applications (Oak Ridge National Laboratory, Argonne National Laboratory)

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Start Date: February 1, 2022 End Date: January 1, 2025
Project Funding: $9,000,000 DOE share: $9,000,000 Non-DOE share: $0

Project Introduction

This project will define and develop the communication requirements to implement energy centric CDA applications, including information messages exchanged, required communication latency, frequency, bandwidth, and other state-of-the-art requirements as well as evaluate their impacts on energy efficiency over a range of scenarios. This effort will directly address concerns identified in the DOE VTO: Roadmap for CDA XIL Test Capability, by establishing a detailed CDA framework that leverages the unique capabilities of DOE's leading XIL national laboratories. The developed and validated communication requirements will drive research in the CDA space and determine the efficacy and energy impacts of CDA on mobility systems.

ORNL and ANL are uniquely positioned to support this effort with a recognized team of experts and embody the DOE EEMS core tools development in SIL, HIL, VIL, and XIL. The team has a proven track record in developing unique controls for connected and automated vehicle technologies, implementing complex algorithms, and developing end-to-end validation methodologies that span from pure analytical tools to direct experimentation on a breadth of dynamometer and vehicle research facilities located onsite at both laboratories.

Objectives

The overall goal of this project is to develop the communication requirements to implement specific CDA applications and methodologies for CDA Classes A-C and utilize them to determine the energy impacts of CDA on selected scenarios. To meet this goal, the following key objectives have been identified:

- In collaboration with the LBNL-led project "Improved Mobility and Energy Savings Through Optimization of Cooperative Driving Automation for Trucks and Passenger Cars in Mixed Traffic Scenarios,"
    - Jointly determine and document current state-of-the-art CDA research and development.

  - Jointly define communication requirements (latency, frequency, bandwidth, etc.) to effectively evaluate CDA scenarios.
- Develop the tools needed (hardware, software, algorithms).
- Quantify through experimentation and simulation the energy impacts of specific CDA applications.

The key project outcomes are listed below:

- Communication requirements to implement Class A to Class C CDA applications and methodologies.
- CDA framework to test and validate novel and existing CDA applications in software, XIL, and fully integrated vehicles and infrastructure.
- Energy impacts of the CDA application and the sensitivity of these impacts to different communications requirements and architectures.

Approach

Task 1 CDA State-of-the-Art Framework and Control Review

Task 1 focuses on laying the foundational groundwork for testing and validation by collecting algorithms and constructing an implementation plan for the agreement-seeking CDA framework. Specifically, the approach to Task 1 will consist of a focus on the following areas:

- Conducting a literature review of state-of-the-art CDA technologies.
- Engage with U.S. DOT to ensure complementary implementations.
- Development of an energy-priority metric to rank-order V2X applications/CDA implementations.

Task 2: Develop and Implement CDA Framework

The overall objective of Task 2 is to develop a communication framework for CDA Class C, agreement-seeking scenarios based on Task 1.1 outcomes. The framework will support message selection and definition for V2V and V2I and will include a multi-step strategy to initiate an agreement request (*who, when, how*), methods to establish sequence and order of V2X messages between various actors (vehicles, infrastructure), a process of how and when a state of agreement is reached, and how actors exchange final intent. Specifically, the approach to Task 2 will consist of a focus on the following areas:

- Development of a full set of representative CDA scenarios.
- Design and implementation of a CDA Class C Agreement seeking negotiating framework.
- Development and expansion of application specific CDA control algorithms.
- Expansion of current XIL hardware infrastructure capabilities, specifically the APACK-I to support select scenarios/CDA implementations

Task 3: System Simulation Evaluation

By combining scenarios defined in Task 2.1 and algorithms developed in Task 2.3 within the CDA framework, a series of tests will be completed to refine and create new communications requirements. This focus on requirements provides opportunities to examine effects on both vehicle and infrastructure within the framework. In addition, integration with accessory toolchains provides additional capabilities related to fault insertion and mitigation. Specifically, the approach to Task 3 will consist of a focus on the following areas:

- Determination of the relative importance of communication requirements in simulation.
- Evaluation of the impacts of communication layer fault insertion.

Task 4: Measure and Verify On-Dynamometer and On-Road Energy Benefits of CDA Benefits While Capturing Communication Sensitivities

With the inclusion of actual vehicle and hardware, impacts of unmodeled dynamics on the CDA algorithms can be well understood. Hardware testing provides insights and feedback to allow readjustment on the CDA algorithms and prepare for the real-world implementation. It also helps characterize and define the communication requirements of the CDA. Specifically, the approach to Task 4 will consist of a focus on the following areas:

- Perform energy centric evaluations of select CDA scenarios in simulation.
- Develop XIL environment and vehicle capabilities to implement CDA and refine communication requirements.
- Exercise XIL within CDA framework to refine communication requirements and complete energy centric evaluation, investigate cross laboratory CDA implementation.
- Development and execution of a comprehensive onsite test plan for controlled roadway energy evaluation at both ORNL and ANL.

Results

Task 1: CDA State-of-the-Art Framework and Control Review

During FY 2023, CDA researchers across the laboratories are involved in Literature Review revision activities prior to final submission into Springer. These are currently ongoing as the topics are split between ORNL/ANL/LBNL/NREL and the reviews are being completed in batches.

Additional efforts by the CDA team included outreach engagement with the US Department of Transportation through DOT CDA activities in the VOICES Community of Practice (COP) working groups. During FY 2023, planning for Event 0 and Event 2 with DOT FWHA was conducted, with both events slotted to take place in FY 2024. In the selected simulation eco-driving scenario shown Figure I.4.1.1, multiple institutions will take part in a collaborate test for various eco-driving algorithms and toolchains. The common simulation platform, CARLA, will be used to host all simulated vehicles in the scenario. All vehicles will exist in simulation only except for ANL's XIL vehicle.

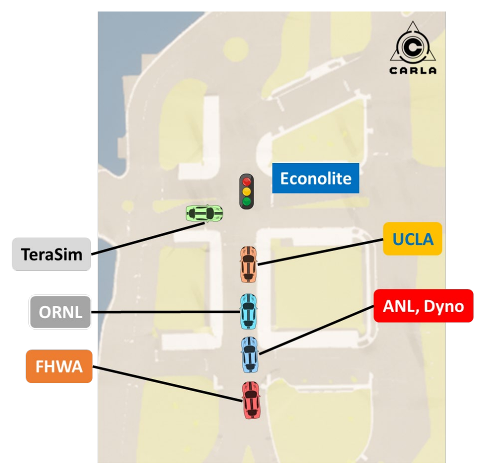


Figure I.4.1.1 DOT VOICES Event 2 Eco-Driving Scenario

In the beginning of FY 2023, the ORNL/ANL team also finalized the development of an energy-priority metric to rank-order V2X applications/CDA implementations. A draft of energy-priority metric was created to capture feedback on energy use impacts of varying CDA scenarios. The metric was shared across joint DOE/DOT/EPA subject matter experts, with a goal of capturing feedback for scenario selection. The results and responses of the energy priority metric were presented in Q1 of FY 2023. The energy priority metric included scenarios from highway, arterial, local, and regional applications with varying areas of focus.

Task 2: Develop and Implement CDA Framework

The objective of this task was to develop CDA scenarios, the communication framework for CDA Class C Agreement Seeking scenarios and developing CDA controls for these scenarios by implementing the framework. Firstly, the CDA representative scenarios development was a three-step process where:

1. High level scenarios were defined using settings, scenes are variations. A combination of factors like road type, traffic signal and sign availability and surrounding traffic situation was used.
2. The energy priority matrix was used to select scenarios that encouraged maximum energy benefits.
3. Control and communication strategies were considered to further streamline the scenarios.

Once the scenarios were selected a V2X communication framework was developed to cater to a wide range of scenarios. The framework draws inspiration from SAE J2735 V2X message dictionary and specifies a set of CDA Messages, data frames and data elements to implement agreement seeking CDA. Additionally, the framework provides ASN1. Notation for the messages, V2X message flow template for exchange of CDA messages between various actors (Figure I.4.1.2), vehicle state flow charts showing show V2X messages trigger vehicle state transitions and pseudo code to aid with deployment of the framework. The framework also considers the 5.9 GHz spectrum's bandwidth limitations to keep data element and data frame sized to a minimum. It also provides guidance on the frequency of transmitting CDA messages.

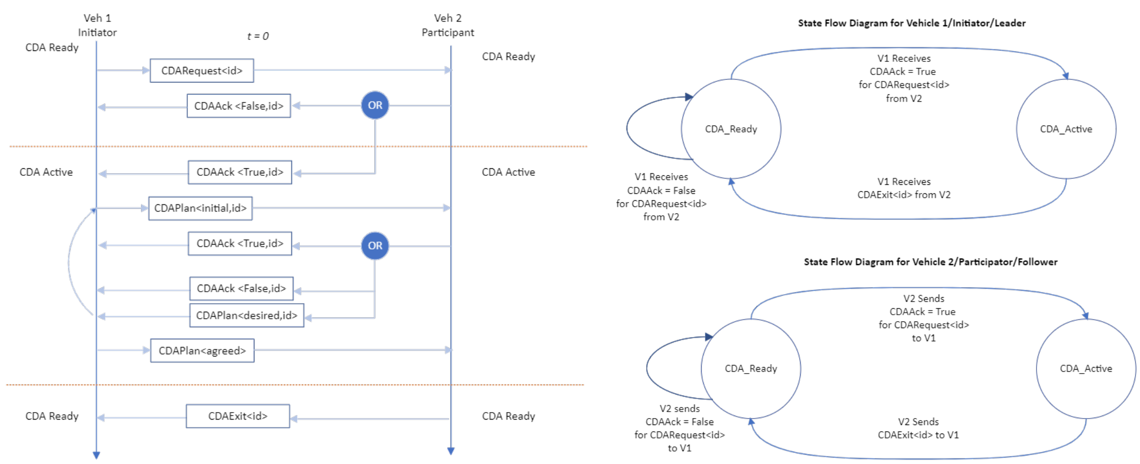


Figure I.4.1.2 V2X communication flow and vehicle state flow

The framework was deployed by ANL on its RoadRunner platform to work seamlessly with CDA controls developed for the Cooperative Car Following scenario. In Task 3, we do a deep dive on the effect of communication parameters on CDA controls performance and analyses tradeoffs between various parameters to provide guidance on desired frequency of CDA messages for performing optimal CDA controls. During FY 2022, we developed control algorithms for agreement-seeking cooperation to reduce vehicle energy consumption in car-following scenarios, which requires autonomous decision-making by CAVs to decide their participation in cooperative driving, as shown in Figure I.4.1.3.

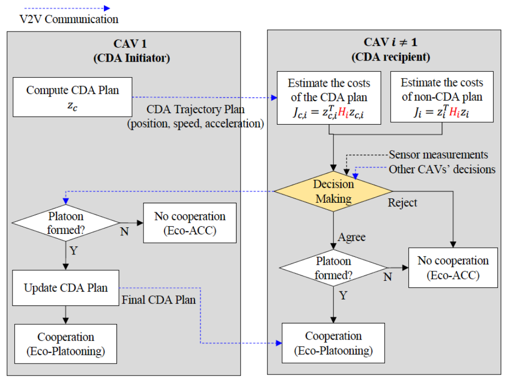


Figure I.4.1.3 Schematic diagram of CDA Class C agreement-seeking cooperation for platoon formation

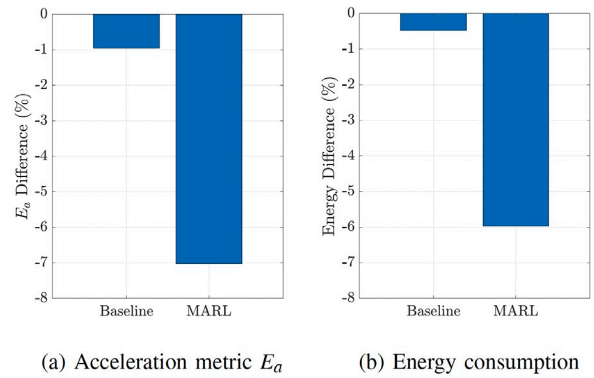
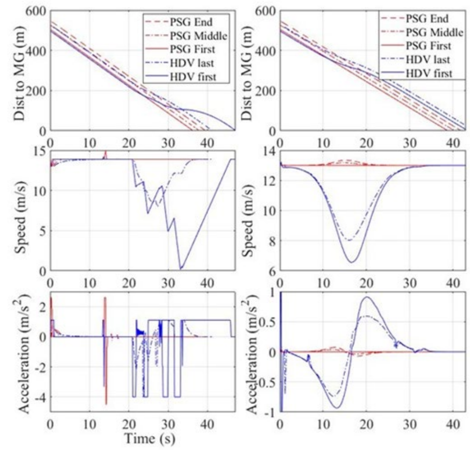


Figure I.4.1.4 System optimality in terms of (a) acceleration energy and (b) energy consumption resulted from different decision-making strategies.

In FY 2023, we developed rational and advanced decision-making strategies to enable CAVs to decide on the CDA plan automatically. We developed two types of decision-making algorithms: a rule-based heuristic algorithm and multi-agent reinforcement learning (MARL). The heuristic decision-making algorithm compares estimated costs between individual and cooperative driving plans and follows the one with lower costs. This method is simple and intuitive and does not require pre-learning but can be myopic. To address this, we developed a MARL-based decision-making algorithm based on a state-action-reward-state-action algorithm. Compared to the heuristic rule, the MARL-based algorithm is far-sighted since it evaluates an action-value function when CAVs make decisions. Additionally, the MARL-based method is interaction-aware since the algorithm considers decisions and the current states of other CAVs. Simulation results show that the MARL-based method can increase cooperation rates by 50% on average compared to the heuristic rule when the cooperation duration is 1s. By increasing the chances of cooperation, using the MARL strategy saves trip energy by 6% in mid-sized battery electric vehicles compared to the status-sharing cooperation, while the heuristic rule saves 0.5%, as shown in Figure I.4.1.4 [2].

At ORNL, the team also completed development of a low-level speed planner for Class B cooperative merging [3], [4]. This speed planner uses the Ultra-Local Model Predictive Control technique, such that the speed planner becomes agnostic to the low-level vehicle dynamics and the embedded cruise controller. Specifically speaking, we propose two vehicle-dynamics-free reference speed planners to merge main road and on-ramp vehicles with distinct dynamics characteristics. For the leading vehicle, the proposed speed planner updates its reference speed online such that the actual leading vehicle speed can accurately follow a desired speed profile, under the constraints on the actual speed and acceleration. For each follower, the planned reference speed guarantees that the actual inter-vehicle distance and its derivative can closely follow their desired values, while respecting the limits on the actual speed and acceleration and avoiding collisions. Ultimately, the merged vehicle platoon can pass a merging point with the desired speed, inter-vehicle distance, and merging sequence determined by a tactical-level traffic management system. The major enhancement with respect to the previous version speed planner is that the novel speed planners remain agnostic to vehicle dynamics characteristics.

The left column corresponds to the vehicle trajectories without the speed planning and control algorithm. Large accelerations and drastic speed variations occurred for collision avoidance. Especially, one of the heavy-duty vehicles was forced to a complete stop, which broke the traffic flow. In contrast, the right column indicates the vehicle trajectories with the speed planning and control algorithm enabled. Each vehicle could reach the merging point with the desired merging sequence, speed, and intervehicle distance from the high-level traffic control center. Smooth traffic flow was realized without severe speed fluctuation, which in turn substantially reduced the overall fuel consumption and CO_2 emission.



	Control disabled	Control enabled
Fuel (ml)	5.58E+06	4.27E+06
CO2 (mg)	1.77E+07	1.35E+07

Figure I.4.1.5 Multi-vehicle response

To validate the proposed vehicle-dynamics-free merging speed planners, we execute SUMO/Simulink joint simulations (Figure I.4.1.5). Simulation platform vehicle status from SUMO are first transmitted into Simulink via an S-function programmed based on the TraCI4MATLAB interface. The novel ultra-local model predictive speed planners are formulated and solved via CVXGEN. Particularly, the optimal reference merging speeds are passed through validated vehicle dynamics blocks before feeding back to SUMO to update the longitudinal speed of the simulated vehicles. Note that SUMO traffic simulation does not contain vehicle dynamics by itself and could incur unrealistic longitudinal behavior. Integrating vehicle dynamics blocks with SUMO traffic simulation enables us to validate the performance of cooperative merging speed planners under the influence of distinct vehicle dynamics. This environment is also leveraged to build and develop in parallel to this effort for improving fuel saving, safety, and congestion mitigation of CDA platooning [5].

Additionally, the ANL mobile DAQ (ALPACA) was upgraded to support testing activities for CDA. The V2X radios were upgraded to C-V2X, in line with Federal Communications Commission directives. The radios were enabled with point-to-point transmission of custom CDA messages over the PC5 sidelink and interfaces were developed for communication between the radio and prototype vehicle controller. HIL tests were also performed to characterize the latency of the entire system. The vehicle to be used for CDA testing was selected and instrumented with hardware for CAN overrides and dyno testing has been scheduled soon.

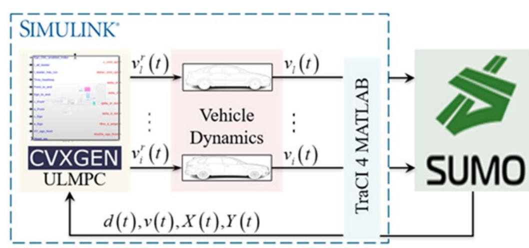


Figure I.4.1.6 Simulation platform

Task 3

Our study aimed to understand the communication requirements for agreement-seeking cooperation by investigating the effects of V2V communication metrics. To achieve this, we incorporated communication-related features into RoadRunner and simulated various communication metrics such as V2V transmission frequencies and CDA message packet drops. The agreement-seeking cooperation control system was updated to address different inter-packet delays. We then conducted large-scale simulations with RoadRunner to assess the impacts of communication metrics on CDA performance in different scenarios. Our simulations involved varying the communication frequency, packet drop ratio, driving scenario, and cooperation duration in 576 cases. Based on our findings, we recommend ensuring a frequency of higher than 10 Hz for agreement-seeking cooperation to maximize the system performance. This would help ensure the validity of messages, reduce the time consumed for agreement-seeking, maximize the cooperation ratio while minimizing the occurrence of false cooperation, and save energy. Figure I.4.1.6 displays some results, and further information can be found in the FY 2023 Q3 report.

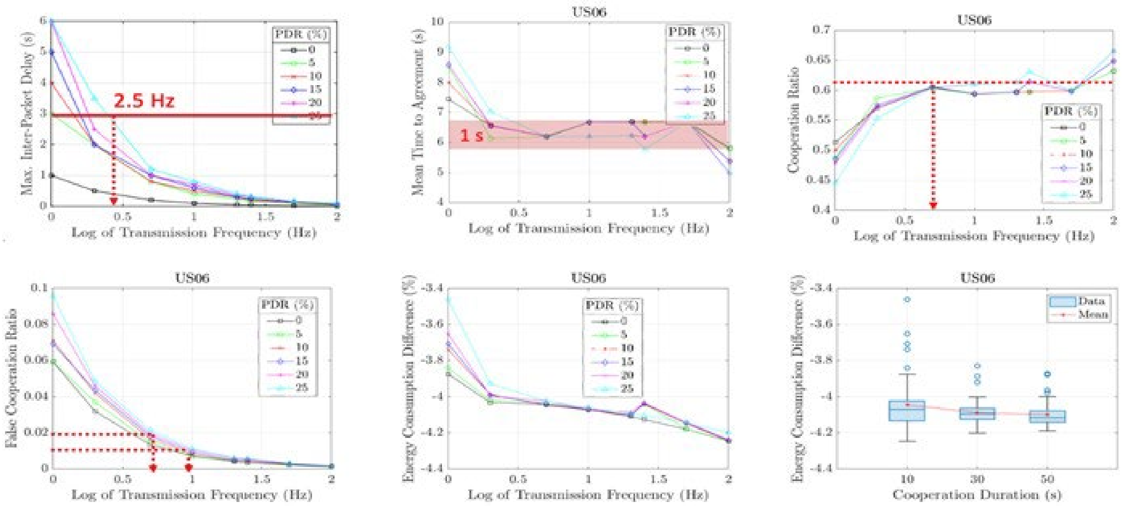


Figure I.4.1.7 Maximum PDR per V2V communication frequency with the maximum error <0.5 m

For the cooperative merging scenario, we first compare the inter-vehicle distance tracking errors per packet drop rate and V2V communication drop rate. It is found that a higher packet drop ratio (PDR) yields deteriorated tracking performance, especially when the V2V communication frequency is low. Moreover, the string stability is not maintained. With the help of a mitigation strategy, the previously mentioned model-free cooperative merging controller can yield almost consistent performance with PDR up to 25%. The maximum PDR per V2V communication frequency, which limits the maximum error within 0.5 m is summarized in Figure I.4.1.7.

V2VC Frequency	25Hz		50Hz		100Hz	
	Prediction OFF	Prediction ON	Prediction OFF	Prediction ON	Prediction OFF	Prediction ON
HDV2	5%	>25%	>25%	>25%	>25%	>25%
PSG1	10%	>25%	>25%	>25%	>25%	>25%
PSG2	5%	>25%	20%	>25%	>25%	>25%
PSG3	5%	>25%	>25%	>25%	>25%	>25%

Figure I.4.1.8 Results of large-scale simulations in RoadRunner with different CDA message transmission frequencies (from 1-100 Hz), packet drop ratios (from 0-25%), and cooperation duration (10-50 s).

Task 4

The ANL team has embedded agreement-seeking cooperation control systems in the RoadRunner environment to evaluate energy consumption using high-fidelity models. This task is an essential step towards our next task of XIL testing by streamlining a model building process and enable testing to be more efficient and accurate. We validated the developed system through RoadRunner SIL tests using various parameters and scenarios. Following successful SIL tests, V2X HIL tests are currently under progress. For this test, the V2X signals were rerouted via real C-V2X radios while the scenario simulation was running in RoadRunner. The HIL tests will help us understand current limitations of the standalone controller and V2X hardware interfaces. Updates are being made to the interfaces to ensure seamless transition from SIL to HIL, VIL and on-road testing in the future. The ORNL team leveraged the Real-Sim toolchain to build a co-simulation of SUMO and Simulink leveraging the dSPACE SCALEXIO system as a real-time XIL unit. In this configuration, a successful test of the cooperative driving merging algorithm was completed using simulated V2V and V2I communication. In the next steps, real time communication using Commsignia V2X radios will be utilized to test the algorithm with real hardware. This will require adaptation of custom messaging with the provided Commsignia C SDK with previously developed software for cooperative control. In addition, improvements to Real-Sim to enable simulation of cooperative scenarios are being completed.

Conclusions

The FY 2023 effort included refinement of the original multi-lab literature review written in the FY 2022. Extending on this work, a rank-order metric was completed and presented as a representation of scenarios of interest for future research. This directly guided scenario selection and development activities, as each lab began to investigate cooperative control in various application areas such as platooning and cooperative merging. Continuing efforts in FY 2022, heavy refinements to CDA algorithms at both laboratories were completed while maintaining changes to the draft CDA framework. The algorithms, scenarios, and framework will be developed in unison moving forward. Furthermore, these tasks were continued into FY 2023 and moved in XIL (RoadRunner and Real-Sim) for further testing and subjected to real hardware, vehicle dynamics, and latencies.

Key Publications

1. E. Hyeon, D. Karbowski, and A. Rousseau, “Potential Energy Saving by Different Cooperative Driving Automation Classes in Car-Following Scenarios,” Proceeding of American Control Conference, San Diego, CA, May 2023.

2. E. Hyeon, D. Karbowski, and A. Rousseau, “Decision-Making Strategy Using Multi-Agent Reinforcement Learning for Platoon Formation in Agreement-Seeking Cooperation,” Proceeding of IEEE Intelligent Vehicle Symposium, Anchorage, AK, June 2023.

3. Z. Wang, A. Cook, Y. Shao, G. Xu. and J.M. Chen, “Cooperative Merging Speed Planning: A Vehicle-Dynamics-Free Method,” 2023 IEEE Intelligent Vehicles Symposium (IV), Anchorage, AK, June 2023.

4. Z. Wang, A. Zhou, A. Cook, Y. Shao, G. Xu, and J.M. Chen, “Energy-Centric Cooperative Onramp Merging Strategy: An Analytical Solution.” Proceeding of 2023 IEEE International Automated Vehicle Validation Conference, Austin, TX, October 2023.

5. A. Zhou, Z. Wang, and A. Cook, “Model Predictive Control-Based Trajectory Shaper for Safe and Efficient Adaptive Cruise Control,” Proceeding of 2023 IEEE International Automated Vehicle Validation Conference, Austin, TX, October 2023.

I.4.2 Improved Mobility and Energy Savings Through Optimization of CDA Application in Signal Controls for Arterial Mixed Traffic Scenarios (Lawrence Berkeley National Laboratory, Argonne National Laboratory, National Renewable Energy Laboratory)

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Start Date: May 1, 2022 End Date: April 30, 2025
Project Funding: $5,000,000 DOE share: $5,000,000 Non-DOE share: $0

Project Introduction

Connection is the key to integrate vehicle and highway automation in a large transportation system to optimize the energy consumption, emission, mobility and other factors such as safety. The advantage of full connectivity includes: (a) CAVs can be used as mobile sensors which provide much more accurate/refined traffic information for estimation than traditional traffic detection; (b) CAVs can follow the traffic control rules (such as signals at intersection and onramp of freeways, speed trajectories, lane use etc.) (both freeways and arterials) automatically, which removes the uncertainties of human drivers, and to force other traffic to follow in the mixed traffic situation which is likely to last for a long period of time; (c) CAVs can be used as the control actuator to regulate the traffic to achieve optimal flow in meso/macroscopic systems levels. This project intends to address some those topics in CDA which is the integration of both vehicles and highways and their impact on energy consumption, emission, and mobility.

More specifically, this project will accomplish the following:

1. Literature of automation technologies for both vehicles and highways and any relevant CDA technologies. We will particularly investigate the gaps of the current technologies in CDA development and CDA application needs for the future. The outcomes of the review will include technical review of all CDA-relevant fields, roadmap for the development and deployment of CDA applications, and publication of all the review as a book.

2. Wireless communication LTE-V2X includes: V2V, V2I, I2V and I2I. Here LTE stands for "Long Term Evolution" 4G technology which has been adopted by SAE for the transportation sector. The CDA application requirements determines the information to be passed in the communication packet. The communication protocol will evolve to meet the requirement of CDA application needs.

3. Applications of CDA in active traffic management (ATM): This project will develop a CAV-in-the-Loop arterial corridor multi-intersection optimal traffic signal control for energy saving, emission reduction, and mobility improvement. A real-time simulation with CAVs imbedded will generate the virtual demands for all the intersections for signal control purposes. The energy performance will be evaluated in real-time simulation of traffic level as well as on the individual physical CAVs. Future research in these aspects will need to include the application of CDA for freeway and larger network traffic involving both freeways and arterials. It is noted that CDA applications in network ATM is largely unexplored.

4. Sensitivity analysis of the impact on energy consumption, emission and mobility: This project will use a larger scope of network traffic (with both freeways and arterials) simulation to quantitatively analyze the impacts of critical factors on energy consumption, emission, and mobility. Those factors will include, but not be limited to the market penetration levels of CAVs and communication architectures.

Objectives

The overall goal of the project is the application of CDA technologies such as CACC/platooning and their application for mixed-traffic management on arterials (with connected traffic controllers) and freeways for energy savings, emissions reduction and mobility improvements.

Approach

The approaches of the project will be reflected in the accomplishment of four major tasks below:

Task 1: Evaluate the current state-of-the-art in CDA research, development, and practice

Progresses of Task 1:

- All the review tasks were conducted by two teams through close cooperation before the end of August 2022. The cooperation includes the distribution of focus areas, integration of review papers for the focus areas, and writing review papers for potential publication.
- Submitted publication application forms to Springer-Nature.
- Springer-Nature initially accepted our publication application. We have discussed with Springer-Nature for the book title to be "Cooperative Driving Automation" which will be an independent book instead of a volume of the existing series "Road Vehicle Automation."
- We have hired a technical editor to review and edit all 13 papers to streamline the writing and to match the format requirement of the Springer-Nature book requirements.
- We submitted a journal paper for publication to Transportation Research Part C. The paper is currently under review.

Further actions needed for Task 1:

- We will need to re-submit the publication application due to the book title change.

Task 2: Define the communications requirements to implement optimal CDA applications including V2V, V2I, I2V and I2I

Progress of Task 2:

- Initially accomplished the first list of messages.
- For V2V, we have added warning signals and driver action signals for intermediate stage as ADAS. We have also added more messages for maneuver coordination. The LBNL team is discussing with the ORNL team on the messages for maneuver negotiations. We are still expanding the V2V message list.
- For V2I, messages mainly include vehicle movement relevant for traffic management of freeways and arterials, and the information that could be used for cooperative perception of all vehicle movements by the roadside traffic management system; revision and coordination/sharing with the ORNL team. The V2I messages will be the same for freeways and arterial intersections.
- For I2V, messages mainly include roadside/on-road sensor traffic detection data, and traffic management information that would affect the movement of CAVs. The I2V messages will be different for freeways and arterials due to the differences in traffic management strategies for them.
- For I2I, messages mainly include roadside/on-road sensor traffic detection data and mobile data if available; traffic management information. The I2I message list for freeways and arterials are different.
- For V2I, I2V, and I2I, message sets have been initially defined for integrated freeway and integrated arterial corridor, and for possible integration and coordination of the two systems.
- We are working with SAE committees on the V2X message definition and seek future cooperation on this topic.
- The LBNL team is actively coordinating with the ORNL team for the message set definitions.

Task 3: Develop the hardware, software, algorithms, and/or methods to implement specific applications of CDA for one or more CDA Classes.

Progress of Task 3:

The activities and accomplishment for this task are outlined below:

- The LBNL team has finalized the Concept of Operation which include all aspects for the system development and field test. Figure I.4.2.1 shows the overall picture for the Concept of Operation.

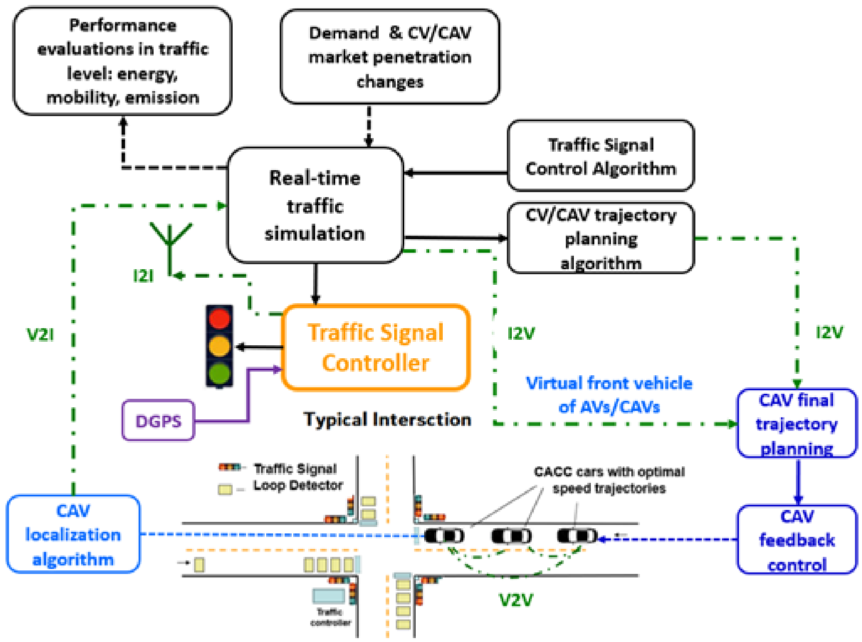

Figure I.4.2.1 Finalized overall system picture for the Concept of Operation (ConOps)

- Overall system structure: We have been developing a feasible overall system structure and Concept of Operation (ConOps) which will be used as the blueprint of Task 3.
- Test track design (Figure I.4.2.2) and simulation modeling: we decided to use the freeway circle of ACM for traffic signal tests.
- ACM will use the project funding to upgrade the facility including LTE-V2X RSU, traffic signal, control cabinet, power. ACM M60 traffic controller will be used.
- Traffic signal control algorithm development: We have used an MPC approach for the algorithm design. It has been implemented in Aimsun as an API and evaluated the performance which is positive.
- Real-time simulation to generate traffic with three physical CAVs imbedded to activate the traffic signals: An initial mixed traffic real-time simulation has been built.
- Localization for CAV: In addition to DGPS, we are using Mobileye for the perception of the front lane marker on the leader vehicle of the platoon for localization, which provide the ground truth of the vehicle position and angle with respect to the lane center.
- CAN override and vehicle shipping: ANL has successfully completed the CAN override development for the three selected test vehicles which have all been shipped to Berkeley, California. This capability grants full authority over the vehicle commands and allows testing and experimentation of custom CACC control algorithms. Test vehicles encompass various powertrain: Toyota Camry (ICE), Toyota Prius (hybrid), and Nissan Leaf (EV)
- LBNL has implemented CACC on two cars and driver vehicle interface.
- LBNL will accomplish the initial system integration (proof of concept) including almost all components for a single intersection before moving to ACM by December 31, 2023.

- ANL has initiated the development of cross-dyno communication capability to support a two-vehicle coordinated XIL testing scenario scheduled for FY 2024. Aimsun, will be integrated into Argonne's existing setup to simulate various traffic scenarios the two vehicles will partake in. This aims to improve energy savings in CACC control algorithm.

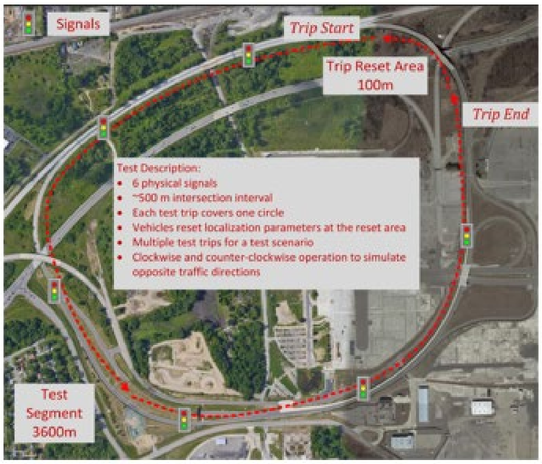

Figure I.4.2.2 **Left:** ACM test track to be used for intersection traffic signal tests: six traffic signal locations; **Right**: ACM facility: locations of traffic control cabinets (green dots)

Task 4: Quantify the energy impacts of CDA application and the sensitivity of these impacts to different communications requirements and architectures in microscopic traffic simulation.

Progress of Task 4:

Activities and plans for this task are outlined below:

- We have modelled US 101 (freeway) and SR 82 (El Camino Real - arterial).
- We have accomplished the model calibration with the GEH flow criteria.
- We have implemented AV and CAV microscopic vehicle following models in simulation: CACC of ICE passenger cars and trucks and ACC model of EVs, which are all based on field experimental data.
- We have selected the wireless communication model and initially implemented. We have achieved the following for wireless communication modeling and simulation:
    - Identified LET-V2X simulator in ns-3.12. We are working with Saxton Lab to model the LTE-V2X wireless communication in ns-3.
    - We went through the code and identified six limiting assumptions of from one. We proposed solutions to address most of the limiting factors to make it more realistic.
    - We identified the Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) developed through multiple DOE projects as the co-simulation framework to federate co-simulation of wireless communication and traffic systems.

- Developed a Python wrapper for ns-3 which can enable manual control over data flow into or out of ns-3 and connected the wrapper to HELICS.
- Worked with Aimsun to enhance V2X SDK to enable co-simulation with ns-3.
- Was able to initiate, pause, modify, and output the ns-3 LET-V2X simulation.

- We conducted initial energy consumption and emission modeling for the evaluation of the performance with the field data from the past projects with FASTSim model.
- Coordinated with ORNL team on network mixed traffic and communication modeling and sensitivity analysis.

Conclusions

All the four tasks of the project are on schedule and within the budget. For Task 1, we have accomplished the review and submission at the end of August 2022. The remaining work is to publish the reviews as a book of Springer-Nature. We have initially defined the messages for V2V, V2I, I2V and I2I for freeway and arterials which will be extended and refined further. We have developed the Concept of Operations as the blueprint for Task 3. We have accomplished most of the development of CACC vehicles, algorithm for optimal signal control and trajectory planning of multiple intersections, localization of CACC vehicles for mapping them into real-time microscopic mixed traffic simulation in Aimsun, real-time simulation, LTE 4G V2X and traffic signal control set up, system integration for test, and extensive systematic tests. For Task 4, we have modeled a network involving both freeway (US 101) and arterial (SR 82, El Camino Real) for microscopic simulation of mixed traffic with sensitivity analysis. We are still working on the modeling and simulation of V2X. Performance evaluation parameters for energy consumption, emission, and mobility have been selected.

Key Publications

1. M. Yang, M. Rawoof, X. Kan, K. Yagantekin, X. Y. Lu, Modeling Commercial Adaptive Cruise Control (ACC) on Multi- Lane Facilities by Incorporating Receiving-lane-change Car-following, TRB 2024 Annual Meeting, Washington D. C. Jan 7–11 2024
2. H. Liu, A. Kurzhanskiy, W. Hong, and X. Y. Lu, Integrating Vehicle Trajectory Planning and Arterial Traffic Management to Facilitate Eco-Approach and Departure Deployment, TRB 2024 Annual Meeting, Washington D. C. Jan 7–11 2024
3. Hao Liu, Alex A. Kurzhanskiy, Wanshi Hong, Xiao-Yun Lu, Integrating Vehicle Trajectory Planning and Arterial Traffic Management to Facilitate Eco-Approach and Departure Deployment, presented at Automated Road Transportation Symposium (ARTS-23), San Francisco, July 9–13, 2023
4. Xiao-Yun Lu, John Spring, Hao Liu and Steven Shladover, C-V2X Message Definitions for Integrated CDA and Active Traffic Management, presented at Automated Road Transportation Symposium (ARTS-23), San Francisco, July 9–13, 2023

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II Connectivity and Automation Technology

II.1 Funding Opportunity Announcements

II.1.1 CIRCLES: Congestion Impacts Reduction via CAV-in-the-loop Lagrangian Energy Smoothing (University of California, Berkeley)

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Heather Croteau, DOE Technology Development Manager
U.S. Department of Energy
Email: heather.croteau@ee.doe.gov

Start Date: January 1, 2020 End Date: December 31, 2023
Project Funding: $4,991,896 DOE share: $3,499,906 Non-DOE share: $1,491,990

Project Introduction

The energy efficiency of today's vehicular mobility relies on the un-integrated combination of 1) control via static assets (traffic lights, metering, variable speed limits, etc.); and 2) onboard vehicle automation (ACC, ecodriving, etc.). These two families of control were not co-designed and are not engineered to work in coordination. Recent studies have shown limitations of controls, and even negative impacts of ACC [1]. The project focuses on the technology development, implementation and prototyping, and validation of mobile traffic control (MTC). MTC can be viewed as an extension of classical traffic control (in which static infrastructure actuates traffic flow). In the MTC paradigm, automated vehicles actuate the entire flow via their behavior, offering enhanced possibilities to optimize the energy footprint of traffic, if designed correctly.

We demonstrated for the first time that considerably reduced fuel consumption of all vehicles in traffic can be achieved via distributed control of a small proportion of CAVs. Compared to baseline vehicular technologies, our work offers a significant design departure: control algorithms for the CAVs consider the impact one vehicle can have on overall traffic, improving resulting overall fuel consumption. We focused on using a few vehicles as traffic controllers via CAV technology) to improve the energy efficiency of traffic flow to further optimize energy efficiency. The demonstrated technology indicates energy savings for all vehicles on the road, with automation of less than 5% of the vehicles in the flow, with the quantitative results awaiting peer review. This estimate is based on our prior field experiments that demonstrated fuel consumption reductions of up to 40% on a single lane track under ideal conditions [2]; which was expected (based on model- and simulation-based estimates) to be reduced in realistic highway conditions due to lane changing and other drivers' responses to actuation.

Objectives

The objective of this project was to develop and demonstrate AI- and theory-based control algorithms that smooth traffic flow in stop-and-go traffic conditions capable of providing ≥10% energy savings. In this project, we developed control algorithms using a variety of techniques ranging from classical control theory to deep-RL, which allowed our control vehicles to cooperatively smooth stop-and-go waves in a real highway environment with live traffic. The team is subdivided into cross-collaborative and cross-functional teams, each spanning multiple institutions and time zones, with slight modifications from the prior year:

- In-Situ Field Testing; primary contributors: all institutions
- I-24 Testbed Development & Computer Vision; primary contributors: Vanderbilt University and Tennessee DOT
- Energy Modelling; primary contributors: Temple University, Toyota, and Berkeley
- Analysis of Controller Impact; primary contributors: Rutgers University-Camden, University of California, Berkeley
- Hardware; primary contributor: Vanderbilt University and University of California, Berkeley

Approach

The work focuses on mobile actuation of multi-lane traffic. Our approach is 1) establish the minimum sensing and connectivity needs for eliminating traffic waves with mobile actuation, and 2) investigate control requirements to dampen stop-and-go traffic. We will publish data sets of vehicular trajectories with fuel consumption rates to advance high fidelity control strategies. Our approach to achieve our objectives includes:

- Developing mathematical models of the traffic, to enhance understanding of the predictability of stop-and-go waves, with careful investigation of lane changing models.
- Designing sensing systems and estimation algorithms to detect the traffic state using on-board vehicle sensing and/or infrastructure sensor networks.
- Designing control and machine learning algorithms to robustly dampen waves or prevent their amplification, by combining lateral and longitudinal control of CAVs.
- Performing software verification of the models, sensing systems, estimation and control algorithms in simulation and on-board CAVs.

- Investigating intelligent agent design constructs for human–autonomous collectives in mixed autonomy environments.

Results

The final results of the analysis are awaiting peer review and may be subject to editorial embargo prior to publication. This section describes the analysis we performed, the data sources used, and the methods we have developed to provide overall estimation of the impact of this project.

In Situ Field Testing: The MegaVanderTest (MVT). Data over the duration of the field test were recorded from the infrastructure systems (I-24 MOTION and roadside radar units) as well as from on-board controllers integrated by the hardware team. These data are the primary sources on which the results of the project have been analyzed.

- I-24 MOTION trajectory data from the experiment account for as many as 100 TB of raw video data, and 200 GB of trajectory data, across all the days of the MVT. The anonymized trajectories of all vehicles in the flow of traffic will be made available to other researchers.
- In-vehicle data acquisition enabled by the hardware integration with the vehicle fleet, account for a total of 13.7 TB of data were collected over 5 days of driving. Over 1.7 TB were from vehicle CAN data, GPS, and ROS bagfiles. The 12 TB are of dashcam video data.

The press releases regarding the MegaVanderTest produced more than 580 articles and new stories, with a calculated audience reach of more than 1 billion (Figure II.1.1.1). Continued production and reflections made by academic institutions are exemplified in the key stories highlighted in the figure below.

Figure II.1.1.1 Assorted photos depict the ongoing stories covered by Rutgers University-Camden [3], Vanderbilt University [4], Fortune [5], the Associated Press [6], and Tech Xplore [7].

I-24 Testbed Development and Computer Vision. The I-24 MOTION system recorded data for later analysis during several days before, all days during, and several days after the MegaVanderTest in November 2022, for comparisons of results while executing our controllers, vs. days in which controllers were not run. During the past review cycle, careful attention and analysis was paid to evaluating these video data in order to produce the most accurate vehicle trajectory data possible. Recently papers have demonstrated the validity of the I-24 MOTION system, including [8], [9], and [10] have provided valuable contributions to understanding the penetration rates of our control vehicles, and extracting the position, speed, and accelerations of all vehicles in the flow, and the class of vehicle observed, in order to permit at scale energy analysis of the impact of the controllers (Figure II.1.1.2).

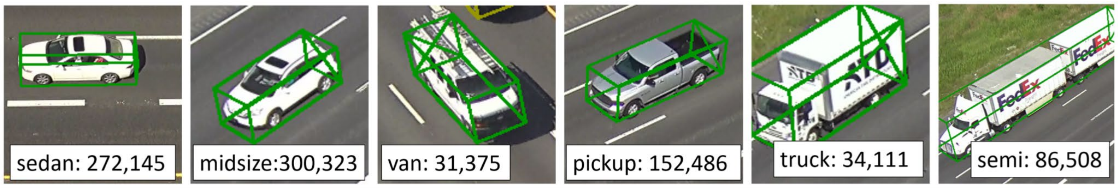

Figure II.1.1.2 Vehicle classification performed by I-24 MOTION permits application of the most appropriate energy models [10]

Energy Modelling. The energy team publicly released the research papers describing the energy models used for fuel consumption estimation and reinforcement learning algorithm training (Figure II.1.1.3). Using I-24 MOTION trajectories, energy models can estimate bulk fuel consumption for different days of the test and use aggregate data to approximate the energy differences when control is off or on, and near or far from our control vehicles (Figure II.1.1.4).

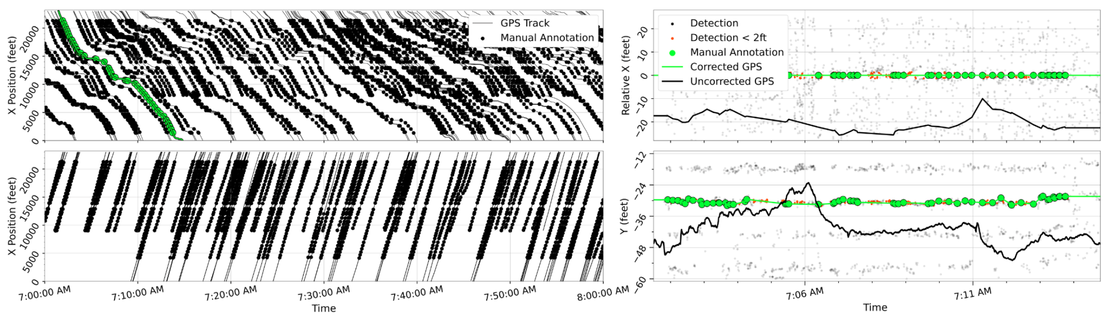

Figure II.1.1.3 GPS data from in-vehicle recording are used by I-24 MOTION researchers to validate vehicle tracking algorithms, and I-24 MOTION is then used to improve GPS data estimates for *post hoc* analysis. From [9].

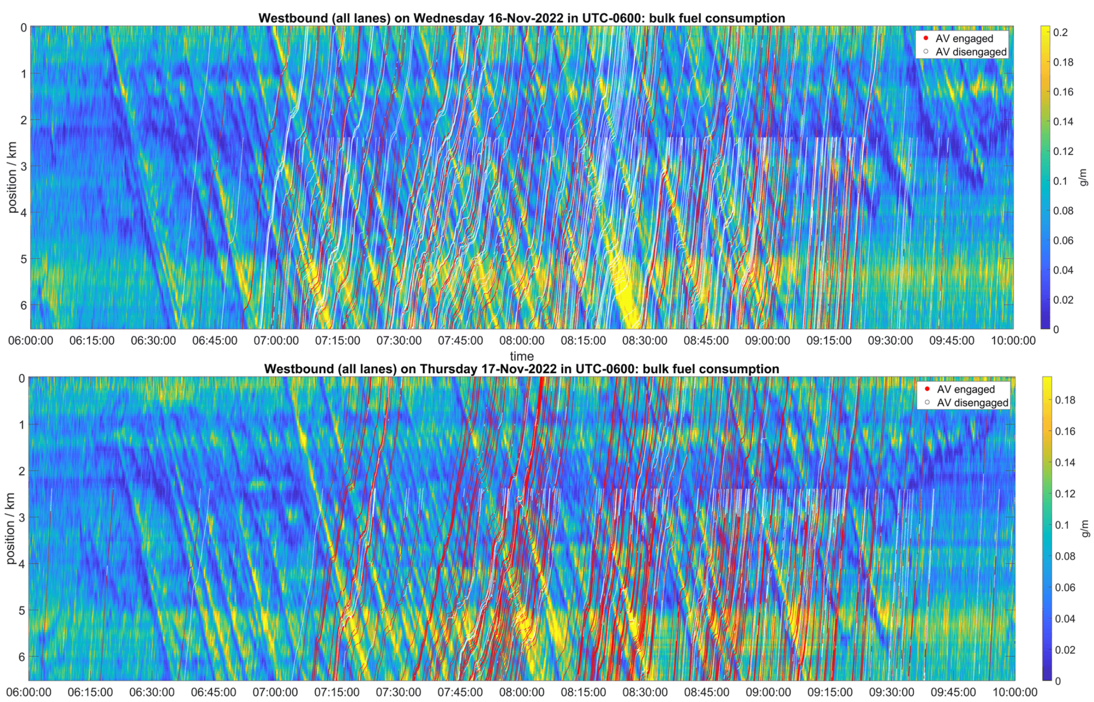

Figure II.1.1.4 Bulk fuel consumption heatmap in time (horizontal axis) and space (vertical axis), based on I-24 MOTION of all vehicles (aggregated over all lanes) driving in the Westbound direction. AV trajectories are overlaid (white: controller not engaged; red: controller engaged). Shown are November 16, 2022 (top) and November 17, 2022 (bottom). From [11].

Analysis of Controller Impact. The analysis of controller impact comes from examining the I-24 MOTION trajectories and looking at how the controller performed *post hoc* based on its design parameters. For each of the controllers we survey preliminary results and present figures from recent submitted papers.

MegaController: Results from Figure II.1.1.4 are explored from the deployment of the MegaController, a hybrid traditional/AI-based controller which ran in different iterations on several days. Penetration rates of the controller in traffic are clearly visible in the time-space diagrams.

Speed Planner: The MegaController depends on the Speed Planner, which evaluates downstream data from traffic provider INRIX, and data from our own vehicles (Figure II.1.1.5). This demonstrates the connectivity benefits of understanding downstream traffic and dampening the wave before the vehicle arrives.

Microaccel controller: This controller was developed using traditional methods which optimized for energy usage benefits through traditional metrics. In Figure II.1.1.6, the smoother trajectories in the lane being controlled by this vehicle are clear, when compared to waves in the neighboring lane at the same time.

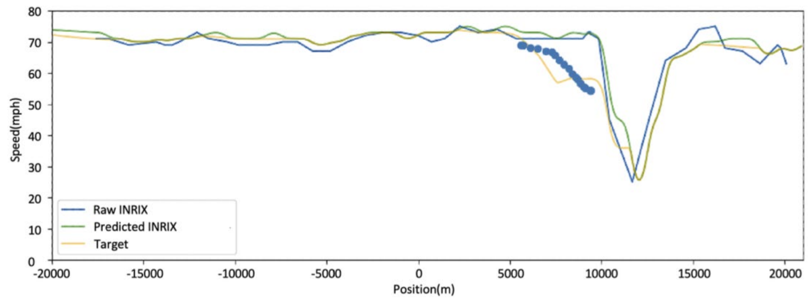

Figure II.1.1.5 The Speed Planner speed. Target speeds to dampen the waves (in yellow) are followed by a control vehicle (blue dots) as it approaches the traffic wave. From [12].

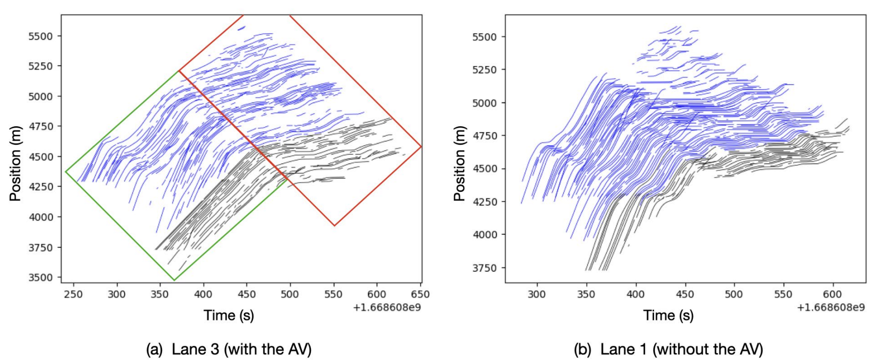

Figure II.1.1.6 Time-space diagrams showing the trajectories of the vehicles up to 400 m upstream (black) and up to 1400 m downstream (blue) of the AV on two different lanes. (a): The trajectories are shown from the AV's Lane (lane 3). (b): The trajectories are shown from another lane without an AV (lane 1). The green box on figure (a) indicates the region where the AV completely absorbs the wave. From [13].

Hardware. Data gathered by the Hardware team were used for overall energy validation and analysis of penetration rates, impact on local vehicle behaviors, and validation of the I-24 MOTION camera system. The hardware design enabled 100 vehicles to execute 19 algorithms, which drove 22,752 miles in 1,022 hours, over 5 days. A video regarding the hardware and vehicle integration innovations is described at [4].

Conclusions

As of this writing, we have completed all four of Budget Period 3's milestones. Milestone 3.4 was completed during the no-cost extension granted for 2023 in the portfolio of analysis techniques applied to the data. Our team will be working to submit the analysis work for peer review in the final quarter. Continued analysis and discoveries will continue beyond the life of the project and beyond the project team and is enabled by our open-source tools and published datasets. As a part of the CSM publications, we are releasing to the public a dataset from the MVT. This data release will include data collected by the AVs as well as the I-24 MOTION system. Where possible, these data will be mirrored on DOE servers.

Key Publications

1. J.W. Lee, et al., "Traffic smoothing via connected & automated vehicles: A modular, hierarchical control design deployed in a 100-cav flow smoothing experiment," submitted to *IEEE Cont. Sys. Magazine*, 2024.

2. N. Khoudari, et al., "A Systematic Model Reduction Pipeline from Detailed Vehicle Energy Dynamics to Simple Models with Desirable Physics-like Properties," submitted to *IEEE Control Systems Magazine*, 2024.

3. H. Wang, et al., "Hierarchical speed planner for automated vehicles: A framework for Lagrangian variable speed limit in mixed autonomy traffic," submitted to *IEEE Control Systems Magazine*, 2024.

4. A. Hayat, et al., "Traffic smoothing using explicit local controllers: Dissipating stop-and-go waves with a single automated vehicle in dense traffic: experimental evidence," https://arxiv.org/abs/2310.18151.

5. M. Ameli, et al., "Designing, simulating, and performing the 100-AV field test for the CIRCLES consortium: Methodology and Implementation of the Largest mobile traffic control experiment to date," submitted to *IEEE Control Systems Magazine*, 2024.

6. K. Jang, et al., "Reinforcement Learning Based Oscillation Dampening: Scaling up Single-Agent RL algorithms to a 100 AV highway field operational test," submitted to *IEEE Control Systems Magazine*, 2024.

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8. D. Gloudemans, et al., "I-24 MOTION: An instrument for freeway traffic science," Transportation Research Part C: Emerging Technologies, 2023.

9. D. Gloudemans, et al., "So you think you can track?," https://arxiv.org/abs/2309.07268, 2023.

10. D. Gloudemans, Y. Wang, G. Gumm, W. Barbour, and D. B. Work, "The Interstate-24 3D Dataset: a new benchmark for 3D multi-camera vehicle tracking," https://arxiv.org/abs/2308.14833, 2023.

11. J.W. Lee, et al., "Traffic smoothing via connected & automated vehicles: A modular, hierarchical control design deployed in a 100-CAV flow smoothing experiment," submitted to IEEE Cont. Sys. Magazine, 2024.

12. H. Wang, et al., "Hierarchical speed planner for automated vehicles: A framework for lagrangian variable speed limit in mixed autonomy traffic," submitted to IEEE Control Systems Magazine, 2024.

13. A. Hayat, et al., "Traffic smoothing using explicit local controllers: Dissipating stop-and-go waves with a single automated vehicle in dense traffic: experimental evidence," https://arxiv.org/abs/2310.18151, 2023.

14. K. Jang, et al., "Reinforcement Learning Based Oscillation Dampening: Scaling up Single-Agent RL algorithms to a 100 AV highway field operational test," submitted to IEEE Control Systems Magazine, 2024.

15. N. Khoudari, et al., "A Systematic Model Reduction Pipeline from Detailed Vehicle Energy Dynamics to Simple Models with Desirable Physics-like Properties," submitted to IEEE Control Systems Magazine, 2024.

Acknowledgements

The project PIs thank Senior Project Manager, Dr. Jonathan Lee, for his leadership during the entire project. The team is grateful to the US DOE leadership, to institutional deputies and administrative staff, our partners at Nashville DOT and Tennessee DOT, and in industry at Toyota, GM, and Nissan.

II.1.2 Human Factors and Technologies Design to Improve User Acceptance of Pooled Rideshare (PR) for Increasing Transportation System Energy Efficiency (Clemson University)

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Start Date: October 1, 2020 End Date: March 30, 2025
Project Funding: $2,500,000 DOE share: $2,000,000 Non-DOE share: $500,000

Project Introduction

Rideshare is being boosted by the dramatic development of TNCs such as Uber, Lyft, etc. The new transportation model provides a large potential to reduce the energy consumption of our transportation systems due to rideshare, especially for the adoption of pooled rideshare (PR). However, in reality, the user acceptance of pooled rideshare is still below expectation, although the TNCs have been developing and expanding quickly. This greatly hinders the impact of the new transportation model on improving transportation energy efficiency. This project will discover the human factors barriers to user acceptance of pooled rideshare and investigate innovative technologies to improve the user acceptance of the state-of-the-art pooled rideshare based on human factors studies results in order to improve the energy efficiency of the transportation system.

Objectives

The project's overall goal is to increase the pooled rideshare user acceptance by 30% to help increase the efficiency of the transportation system by at least 15%. The main objectives of this project are as follows:

- Complete human factors data collection on pooled rideshare.
- Complete human factors barrier analysis and pooled rideshare user acceptance modeling.
- Complete human factors involved technologies design for improving user acceptance of pooled rideshare.
- Complete the validations and evaluation of the pooled rideshare models and technologies.

Approach

Analysis of Human Factors in Pooled Rideshare

The phase one and phase two survey data from last year were analyzed through a variety of means to glean a greater understanding of the factors affecting pooled rideshare. Techniques include a variety of complex data analysis and modeling methods. First, a structural equation model (SEM) was fit to the phase one survey data, and its mediating (indirect) effects were analyzed to understand the relationship between the independent and dependent variables within the phase one data. The four mediating factors were defined as safety, trust in the service, willingness/attitudes towards PR and service/experience. This analysis revealed significance in 12 different paths between model factors, which each signify an underlying relationship between factors' sensitivities and their contribution towards persons' opinions of PR.

A higher-order factor and multicollinearity assessment were completed to ensure that factors were independent of one another, and the conclusions drawn from the SEM were statistically viable. The SEM model was then used to create a pooled rideshare acceptance model (PRAM). The PRAM allows for the exploration of differences between groups of potential riders from the Phase 1 survey through the addition of moderating factors from the "your transportation needs" and "demographics" sections of the survey. First, a conceptual model was developed by forming paths between the 10 factors (latent variables) explored in the survey, including time/cost, safety, etc., coupled with the two response variables of willingness/attitude and acceptance. A total of 14 paths between these variables were explored, with 11 showing significance. These paths reveal the relationships between factors, for example, the relationship between participants with strong privacy concerns to those with safety concerns. These relationships reveal how factors influence one another within the model, and illustrate that factors compound in hidden constructs that affect persons' overall perceptions and decisions. The underlying covariance-based SEM structure of the PRAM quantifies these effects through moderators. These moderators were separated into 16 categories based on participants' socio-demographic characteristics, including region, age group, ride-sharing experience, etc. The analysis of the human factors barriers in pooled rideshare was completed with the development of the PRAM.

Theoretical Modeling of User Acceptance on Pooled Rideshare

In addition to the barrier analysis, the Phase 2 survey data was used to design and construct models that reflect the likely user acceptance of pooled rideshare based on a variety of socio-economic and trip characteristic factors. The descriptive analysis of the stated choice section of the phase 2 survey was used to identify and select variables with noticeable influence on the selection of pooled rideshare. These factors were then used to construct and fit a binomial logit (BL) choice model, whose output indicates the likelihood of selecting the pooled ride alternative in a choice between a solo and pooled ride. Various additive constructs were explored to attempt to increase the model's accuracy to the behavior reflected in the surveys. These constructs include variable interactions, which illustrate the effects of sensitivities to some variables on others. In this case, two interactive constructs were formed: the interaction of gender and whether individuals were pre-screened for safety and the interaction between trip urgency and extra travel time added by pooling the ride.

A random variable construct was also explored, where model coefficients were fit as normal distributions rather than fixed numbers. The random variable construct allows large populations of homogenous individuals to be more accurately modeled by allowing their sensitivities relative to certain trip characteristics to be comprised of distributions that capture more of the population's hidden underlying variance. After model conceptualization and fitting, the models were then analyzed based on the coefficients, where a positive coefficient indicated that the variable was in favor of choosing PR, and a negative coefficient suggested that the variable hindered user's preference for PR. Sensitivity analyses were also performed to understand how future shifts of factors, e.g., optimization of travel time or application of safety prescreening protocols, can influence the overall adoption rate of PR. The BL model with random effects is designated as the mixed logit (MXL) choice model.

The MXL and BL models fitting performance indicators were compared to one another to determine the best overall model to represent the choice. These performance indicators included the Akaike Information Criterion and the McFadden's pseudo R-squared values. To leverage the analysis and attitudinal constructs illustrated in the PRAM model, with the direct choice output of the choice models, an integrated choice and latent variable (ICLV) model was constructed. This model is first fit in its latent variable model (LVM) portion through a series of ordered probit models. The LVM allows an understanding of the sensitivities of key demographic groups toward their overall attitude in their willingness to consider PR. This LVM's specification required adding some factors previously determined to be insignificant such that the model could be used in future simulation studies whose primary control structures impact time and cost. The choice model portion of the model employed a MXL model to better capture population heterogeneity. By integrating latent variables, trip characteristics, and the interactions between these variables into the specification of the choice model, the ICLV model can generate a comprehensive understanding of the participants' choice behaviors in rideshare services.

Development of Conceptual Experiences and Services

The PRAM model captured relationships between factors influencing the use of pooled rideshare. These results were used to compile an initial list of proposed implications and recommendations to rideshare stakeholders such as regulators and operators. Prior to developing a list of potential recommendations based upon each individual moderator, updates were made to our intensive literature review to capture recently published research in the area, new regulatory information, and current events which impact public perception of rideshare and pooled rideshare.

Currently, the moderators from the PRAM model are being used to create profiles of those most likely to be open to considering pooled rideshare. These analyses aggregate our sample of over 5,000 participants into socio-demographic groups who share common sensitivities to specific moderators. Some factors, including comfort, convenience, and passenger safety were not sensitive to specific groups, indicating that they were significant to all groups. This analysis allows recommendations to be made to operators and regulators on how to address the unique needs and concerns of specific groups.

Pooled Rideshare Simulation, Optimization and Validation Development

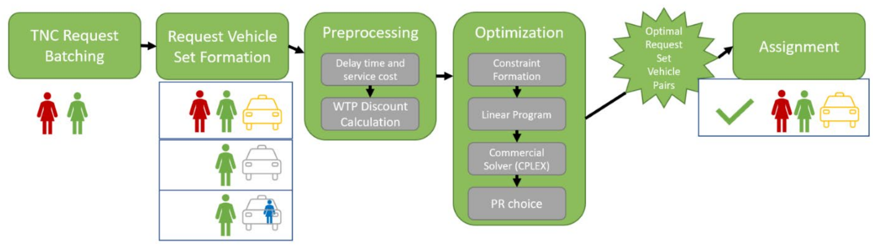

Figure II.1.2.1 Overview of the adaptive assignment algorithm

The development of a novel adaptive fleet vehicle assignment strategy was completed this year. The strategy utilizes the mixed logit choice model to determine the likelihood that simulated riders will accept a ride and then adaptively assign the rideshare vehicles to the riders with appropriate features such as discounts required to incentivize riders to accept the negative level-of-service impacts of utilizing a pooled rideshare over a solo alternative. The strategy aims to improve the discounts offered to potential riders, increasing the likelihood of them pooling while also decreasing the excess cost associated with offering higher-than-needed discounts and non-optimal rider vehicle combinations. Additionally, the strategy was designed for use in a variety of supply/demand imbalance scenarios to maximize the efficiency and profitability of both types of fleets. The strategy uses a multistep process in which a series of potential matches are explored, discounts for pooled rides are estimated, optimal combinations of riders and vehicles are obtained, and acceptance of trips is verified. POLARIS, an agent-based traffic simulation and analysis application, was used to implement and test the discount-based strategy. The strategy was tested in two regional POLARIS models: Austin, Texas and Greenville, South Carolina. An illustration of the algorithm is provided in Figure II.1.2.1. The initial TNC discount strategy utilized just two model factors to estimate the willingness to pay discounts required to incentivize pooling for a particular trip: delay and trip urgency. Additional trip factors such as wait time and trip length, as well as likely known demographic factors such as age and sex, were added to the discount estimation to attempt to cater the predictions more specifically to the ride.

Results

Results of Analysis of Human Factors in Pooled Rideshare

The SEM analysis of user acceptance yielded a result of 11 path combinations of factors being significant. Privacy and safety both had negative indirect effects on trust service and willingness/attitude towards PR. Convenience and trust/service, however, had positive indirect effects on the dependent variables of willingness/attitude and user acceptance. The relationships between factors are displayed in Figure II.1.2.2. A multicollinearity analysis was conducted to identify problems with highly correlated independence variables. The analysis yielded variance inflation factor (VIF) results of under 5 for the time/cost, safety, service experience, and convenience factors for the trust/service construct. Similarly, for the user acceptance of PR independent variable, VIF values for “service experience”, “traffic environment”, “trust service”, “willingness attitude” towards PR, comfort/ease of use, and passenger safety were all under 10, indicating multicollinearity was unlikely.

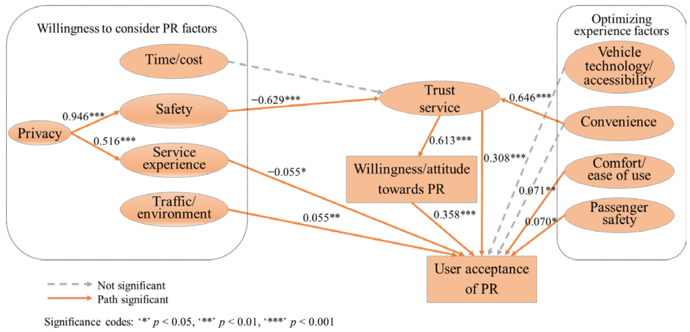

Figure II.1.2.2 The SEM model with significant relational paths

The PRAM model, illustrated in Figure II.1.2.3, yielded 11 significant paths. These paths allowed the model to fit all desired goodness-of-fit metrics and illustrated relationships such as that between service reliability and trust in the service. Many of these relationships correspond with the intuitive relationships between factors. The only two non-significant factors in the model were “time cost” and “vehicle technology accessibility”. Privacy, safety, and service experience were factors that discouraged the use of PR, whereas the convenience factor greatly encouraged the acceptance of PR. Despite the time/cost factor’s lack of significance, individual items related to time and cost were crucial when viewed within the context of convenience. This highlights that user perceptions of privacy and safety are paramount to their attitude towards PR. Once safety concerns are addressed, then topics related to convenience, such as time and cost significantly enhance riders’ trust in pooled rideshare services.

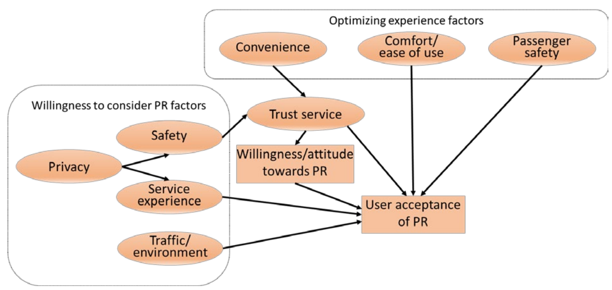

Figure II.1.2.3 PRAM model structure

Results of Theoretical Modeling of User Acceptance on Pooled Rideshare

The BL model was fit to the phase two survey data with a statistically significant χ^2= 17596.9, p < .001 and a McFadden’s Pseudo R-Squared value of 0.067. The model coefficients suggested a series of conclusions regarding the potential acceptance of a pooled ride based on demographic and trip factors. For example, persons with higher household incomes were less likely to choose pooled rides, where riders picked up in the day were more likely to choose pooling than those traveling at night. The sensitivity analysis yielded shifts of PR usage rate with potential factors changes. Table II.1.2.1 illustrates such

Table II.1.2.1 Comparison of fitting metrics between the BL and MXL models

Fit Metrics	*BL model*	*MXL model*
Log-likelihood	-33430	-24614
McFadden’s Pseudo R^2	.067	.264
AIC	66929	49322

Table II.1.2.2 Pooling percentage vs discount rate from the BL model sensitivity analyses.

Change of factor	*Change of PR usage*
Extra 10% PR price discount	+7.5%
Extra 10% PR travel time	-1.6%
Extra one-minute walk for PR	-1.9%
One extra passenger for PR	-2.1%
PR with safety prescreening	+13.6%

relationship shifts. One such shift shows that the pooling rate increases relative to the discount rate, which further encouraged us to investigate innovative discount policies to boost the user adoption of PR. Furthermore, the MXL model was fit, and its metrics were compared to the BL model in Table II.1.2.2, with the former having a log-likelihood of -24614, a pseudo r-squared of 0.264, and an AIC of 49322 compared to the latter's -33429, 0.067, and 66929. Importantly, the MXL model yielded a pseudo r-squared of 0.264, indicating a large heterogeneity across choice behaviors in individuals. The implementation of the ICLV model yielded relationships between demographic groups and the latent constructs, allowing for conclusions such as specific demographic groups that value safety more than others, including low-income and female users. Additionally, the fitting of the utility portion of the ICLV model was fit and illustrated similar trends to those in the BL and MXL models. This model will be continuously refined for better fitting results.

Results of Development of Conceptual Experiences and Services

The PRAM model was developed to allow for data-driven recommendations for fleet operators and regulators. The importance of the privacy, trust, and safety factors demonstrated the importance of increasing user trust in a service, both from a reliability and safety standpoint. Analysis of the moderators' effect on the PRAM yielded a series of relationships and different group sensitivities, as illustrated in Figure II.1.2.4. Possible solutions to overcome rider concerns are being explored. Updates to the literature review included a review of Sami's law and its effect on PR ridership and regulation, as well as user trends and the lingering effects of the COVID-19 pandemic. A workshop with key project partners will select and refine the proposed possible solutions and constructs for the Phase 3 survey slated for BP3.

Moderator		Privacy → Safety	Privacy → Service experience	Safety → Trust service	Service experience → User acceptance of PR	Traffic/ environment → User acceptance of PR	Convenience → Trust service	Comfort → User acceptance of PR	Passenger safety → User acceptance of PR	Trust service → Willingness /attitude towards PR	Trust service → User acceptance of PR	Willingness/ attitude towards PR → User acceptance of PR
Gender		Yes	Yes	-	-	-	-	-	-	-	-	-
Generation		-	-	Yes	Yes	Yes	-	-	-	-	Yes	Yes
Geographic area		-	-	-	-	-	-	-	-	-	-	-
Driver license		-	-	Yes	-	Yes	-	-	-	Yes	-	-
Rideshare experience		Yes	-	Yes	Yes	-	-	-	-	Yes	-	Yes
School completion		-	Yes	-	-	-	-	-	-	-	-	-
Employment status		Yes	-	-	-	-	-	-	-	-	-	Yes
Number of people in the household		-	-	Yes	-	-	-	-	-	Yes	Yes	Yes
Number of children		-	-	-	-	Yes	-	-	-	Yes	-	Yes
Household annual income		-	-	Yes	-	-	-	-	-	-	-	Yes
Number of vehicles		-	-	Yes	-	-	-	-	-	-	-	Yes
Typical transport-ation to commute	Personal vehicle	-	-	Yes	Yes	Yes	-	-	-	Yes	Yes	Yes
	Public transport	-	Yes	-	-	-	-	-	-	-	-	-
	Walk/bike	-	Yes	Yes	-	Yes	-	-	-	-	-	-
	Tele-commute	-	-	-	-	-	-	-	-	-	-	-
	Carpool	Yes	-	-	-	-	-	-	-	Yes	-	Yes

Yes – indicates a significant difference in a moderator.

Figure II.1.2.4 Summary of moderators with influence on the PRAM

Results of Pooled Rideshare Simulation, Optimization and Validation Development

The Greenville, South Carolina POLARIS regional model was completed this year, and its component behavioral models were calibrated against National Household Travel Survey data to reflect the behaviors of travelers in the area as accurately as possible. The Greenville, South Carolina region has a very low share of rideshare usage compared to the Austin, Texas and Chicago, Illinois regions, therefore for the testing of the discount-based strategy, the Chicago variant of the mode choice model was used to increase the share of rideshare such that changes in performance were more apparent. The Greenville model captures the downtown region of the city, work on a comprehensive Upstate, South Carolina model, encompassing Greenville County, and its five neighboring counties, is underway. Figure II.1.2.5 illustrates the extents of the Greenville, South Carolina and Upstate, South Carolina models.

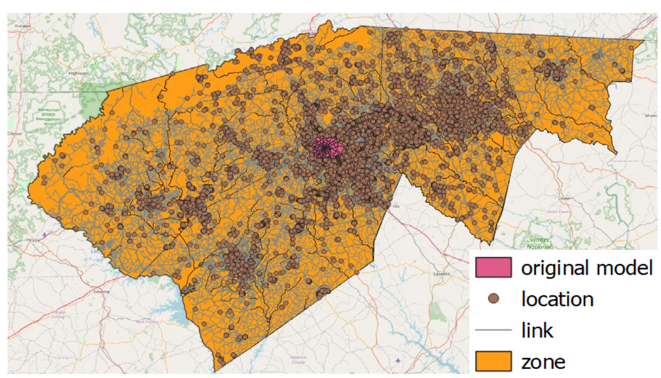

Figure II.1.2.5 The Greenville, South Carolina regional model compared to the Upstate, South Carolina regional model extent

The adaptive discount-based vehicle assignment strategy was first analyzed through a study of its optimization construct by comparing a series of key performance indicators to a baseline heuristic assignment strategy. Preliminary results yielded a notable increase in average vehicle occupancy (AVO), revenue AVO (rAVO), pooling percentage, and revenue coupled with a decrease in empty vehicle miles traveled (eVMT).

The test of the complete adaptive discount algorithm (*D*) was then compared to a baseline heuristic model (*H*), which utilized homogeneous discounts and an optimization-based model with no discounts (*ND*). Results for three different fleet sizes in each of the two test regions yielded an increase in pooling of up to 38.9% versus homogeneous discounts, with a complimentary decrease in eVMT of up to 7.1%, reducing unnecessary traffic from pickup trips. Financial analysis indicated that revenue obtained from fare from the discount strategy was significantly greater than that in the heuristic strategy when the homogeneous discount offer was equal to that of the average of all discounts in the discount strategy cases. This reveals that the discount-based strategy is able to more effectively utilize discounts than the heuristic strategy, increasing efficiency and revenue while decreasing traffic and environmental impacts. The compromise lies in riders accepting longer delays and wait times due to discount incentivization.

Finally, a preliminary study of the addition of additional factors to the willingness-to-pay component of the discount strategy revealed possible improvements to the performance of the model, especially through the addition of demographic factors such as age and sex. Figure II.1.2.6 illustrates the AVO and rAVO obtained from fleets operating with willingness-to-pay structures, including Delay, Urgency, trip Length, additional People, Time of day, Age, and Sex (DULPTAS). The analysis reveals that the DULPTAS strategy had the second-best performances versus the original DU structure and outperformed the DU structure in revenue.

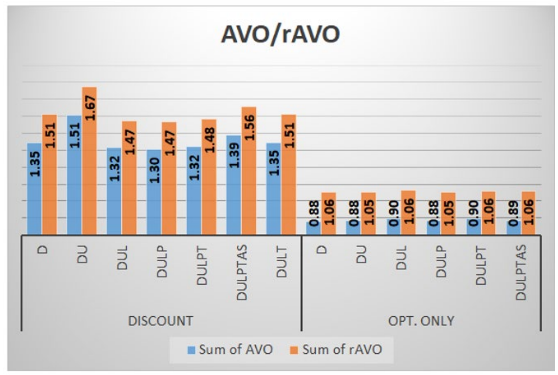

Figure II.1.2.6 AVO and rAVO for additional WTP factors in tests within the Greenville regional mode.

Conclusions

The team has completed data analysis and modeling for the Phase 1 and 2 surveys, including creating BL, MXL, PRAM, and ICLV models. The models were analyzed and used to draw conclusions relating to the adoption of pooled rideshare and the obstacles to increasing its usage. Moderator analysis of the PRAM revealed socio-demographic groups that were more or less likely to have a chance of utilizing pooled rideshare, allowing operators and regulators better targets for marketing such a service. A novel adaptive assignment strategy was implemented and tested, yielding an increase in pooling of up to 38.9%. Further research in the addition of model factors to the willingness to pay structure is underway.

Key Publications

1. Dataset: A National Dataset on Human Choices in Pooled Rideshare. 2022.

2. Dataset: A National and Big City Dataset on Human Factors in Pooled Rideshare. 2021. (Cities include New York, San Francisco, Detroit, Chicago, Atlanta and Austin)

3. Su, H., Khan, N. A., Gurumurthy, K. M., Paul, J., Gangadharaiah, R., Boor, L., Kolodge, K., Auld, J., Brooks, J., & Jia, Y (2024). Analyzing Users' Choice Behaviors in Rideshare Services with Mixed Logit Modeling Method. Transportation Research Board Annual Meeting. (Accepted)

4. Paul J., Gurumurthy K.M., Cokyasar T., Su H., Auld, J., Jia Y. (2024) Integrating Human Factors in Dynamic Rideshare Assignment: Willingness-To-Pay for Delay. Transportation Research Board Annual Meeting. (Accepted)

5. Su, H., Gangadharaiah, R., Rosopa, E., Brooks, J., Boor, L., Kolodge, K., Rosopa, P., & Jia, Y. (2023). An Analysis of Factors and their Impacts on Willingness of Pooled Rideshare. Transportation Research Record.

6. Gangadharaiah, R., Brooks, J., Rosopa, P., Su, H., Boor, L., Edgar, A., Kolodge, K., & Jia, Y. (2023). The Development of the Pooled Rideshare Acceptance Model (PRAM). Safety, 9(3), 61.

7. Su, H., Gangadharaiah, R., Paul, J., Boor, L., Kolodge, K., Gurumurthy, K, Khan, N., Auld, J., Brooks, J., & Jia, Y. (2023). Exploring Demographic Factors behind the User Preferences in Ridesharing Services. IEEE Intelligent Transportation Systems Conference (ITSC), Bilbao, Bizkaia, Spain, Sept. 2023.

8. Paul J., Gurumurthy K.M., Cokyasar T., Su H., Auld, J., Jia Y. (2023) Analyzing Agent-Dependent Delay Time Acceptance in Dynamic Ride Sharing Systems. IEEE Intelligent Transportation Systems Conference (ITSC), Bilbao, Bizkaia, Spain, Sept. 2023.

9. Gangadharaiah, R., Su, H., Rosopa, E., Kolodge, K., Boor, L., Rosopa, P., Jia, Y., & Brooks, J. (2023). Factors Influencing Adoption of Pooled Rideshare: An Explorative Study on User-Centered Design and Services. Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

10. Su, H., Gangadharaiah, R., Rosopa, E., Brooks, J., Boor, L., Kolodge, K., Rosopa, P., & Jia, Y. (2023). Willingness to Consider Pooled Rideshare? An Exploratory Study on Influential Factors. Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

11. Gangadharaiah, R., Su, H., Rosopa, E., Brooks, J., Kolodge, K., Boor, L., Rosopa, P., & Jia, Y. (2023). A User-centered Design Exploration of Factors that Influence Willingness to Consider Pooled Rideshare. Safety, 9(2), 36.

12. Gangadharaiah, R., Mims, L., Jia, Y., & Brooks, J. (2023). Opinions from Users Across the Lifespan about Fully Autonomous and Rideshare Vehicles with Associated Features. SAE Technical Paper.

13. Mims, L., Gangadharaiah, R., Su, H., Jia, Y., Jacobs, J., Sterling, M., & Brooks, J. (2023). What Makes Passengers Uncomfortable in Vehicles Today? An Exploratory Study of Current Factors that May Influence Acceptance of Future Autonomous Vehicles. SAE Technical Paper.

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II.1.3 Co-optimization of Vehicles and Routes (CoVaR) to Improve Commercial Transportation System Efficiency (PACCAR Inc.)

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Start Date: September 24, 2020 End Date: June 30, 2024
Project Funding: $2,500,000 DOE share: $2,000,000 Non-DOE share: $500,000

Project Introduction

PACCAR Inc. (PACCAR Technical Center and Kenworth) and its project partners Esri, Kopius, NREL, and the Ohio State University are working to develop and demonstrate a co-optimization of vehicles and routes (CoVaR) to improve commercial transportation system efficiency. CoVaR is a suite of innovative, co-optimized solutions designed to improve freight energy efficiency through vehicle specification optimization, energy efficiency optimized freight and vehicle routing, driver coaching, reduced deadheading, and improved vehicle utilization to reduce miles driven with partial or no payload.

The key technologies being developed in this project are:

1. Integration of advanced telematics on trucks to collect key performance indicators for fleet energy efficiency and development of a vehicle-to-cloud infrastructure to process telematics data to meaningful insights.

2. Develop a cloud-based physics-driven machine-learning algorithm to leverage the telematics data and co-optimize the supply chain and vehicle specification optimization, by leveraging high-fidelity simulations and planned route information.

3. Develop a cloud-based real-time dashboard/app for fleet managers to diagnose problems with transportation system efficiency and make rapid decisions.

4. Develop a cloud-based intelligent driver assistance system (IDAS) to provide driving coaching for safety, energy, and operations efficiency.

Objectives

Overall Objectives:

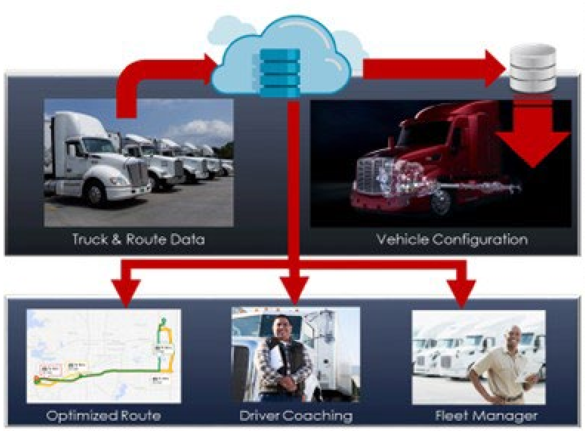
The goal of this PACCAR led project is to demonstrate a 25% reduction in fleet brake-specific energy per freight ton-mile (kWh/ton-mi) relative to a 2020 baseline by developing an innovative solution which leverages intelligent transport systems and cloud computing. The energy efficiency improvements will come from 1) fleet duty cycle specific vehicle specification optimization, 2) fleet management to reduce deadheading for improved goods transportation energy efficiency, and improved vehicle utilization to reduce miles driven with partial or no payload, and 3) driver assistance for improved freight and vehicle routing (eco-routing) and 4) eco-driving. The technology will be demonstrated on a large field test with a commercial fleet partner of 50 vehicles.

Fiscal Year 2023Objectives:

- Development of key technologies including:
  - Energy efficient routing.
  - Driver coaching.
  - Powertrain recommender system.
  - Fleet management system/dashboard.
  - Cloud architecture.
- Evaluate and select on-board telematics, compute, and display hardware.
- Onboard a fleet partner for a 50-truck field test during 2023.
- Implement a proof-of-concept demonstrator truck for initial testing and validation of technologies.
- Baseline fleet data evaluation and impact assessment of new technologies related to freight energy efficiency improvements.

Approach

The project has utilized a system engineering approach for the development and integration of several technologies centered around connected vehicle analytics to improve fleet freight energy efficiency. The key development areas are energy efficient routing, driver coaching, powertrain configuration optimization, fleet management, cloud architecture, and advanced telematics. The team is also using the Technology Readiness Level process to evaluate the new technologies for production and commercialization. A representative project overview can be seen in Figure II.1.3.1 and Figure II.1.3.2.



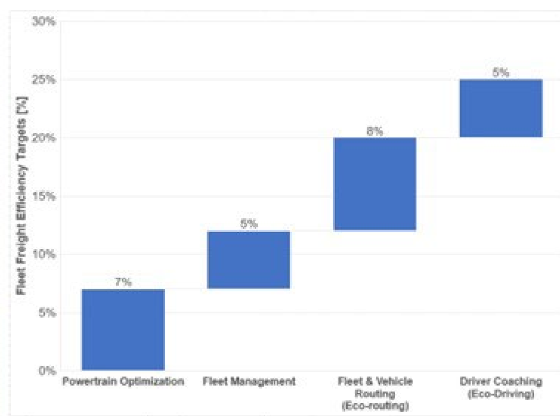


Figure II.1.3.1 Waterfall graph of energy efficiency targets

Figure II.1.3.2 Targets overview of CoVaR data flow

While telematics development is commonplace in the automotive industry at this point, there are still several challenges that remain in terms of high cost and frequency of data collection. The challenge and goal for this program related to telematics is to find the best telematics solution in terms of cost, performance, and scalability. This involves the technical assessment of several commercial off the shelf devices as well as internally developed solutions. The main function of this portion of the program is to aggregate and process vehicle CAN data and route it to the in-cab display and cloud for further processing.

The IDAS combines the energy efficient routing and driver coaching aspects into a user-friendly application ran on the in-cab display. The energy efficient routing, or eco-routing, feature will provide the driver with a route optimized for energy efficiency, based on NREL's RouteE tool and Esri's ArcGIS software. The route may not be the shortest time or most energy efficient but will be the optimal tradeoff between the two. The IDAS will also display driver coaching metrics pre and post trip to help encourage more fuel-efficient driving. The metrics will allow the driver to gauge their performance immediately after completing a drive.

The goal of the Powertrain Recommender System (PRS) is to provide a set of pareto-optimal powertrains to customers based on their performance requirements, energy efficiency, freight capacity, selling price, or other factors. The PRS will utilize historical data to train machine learning models to predict energy consumption for various powertrain models and provide the optimal recommendation for a fleet.

The fleet management system and dashboard will provide a fleet manager with real-time performance metrics and status updates (i.e., route location) to allow for the fleet manager to adjust as needed to reduce deadheading and non-optimal freight movement. This dashboard will get real-time data updates from the fleet via the cloud and provide more opportunities for energy improvement. While the focus of the dashboard is on energy efficiency, it could also lead to early notification of performance issues if certain trucks are consistently performing worse than others.

Results

The major focus of the CoVaR project has been on the technology development side. Each of the technologies mentioned previously have gone from initial concepts through design phases and prototypes. One major milestone of the technology development phase is a demonstration truck being operated at the PACCAR Technical Center to test the developed technologies. Below is a summary of each technology's development throughout the program to date.

Telematics & Cloud Infrastructure

Several commercial off the shelf telematics units, dataloggers, edge compute devices, and architectures were researched and assessed based on technical capability, cost, and scalability. The main goals and functions of the telematics portion of this program are to collect and aggregate high-resolution vehicle CAN data, perform processing / edge computing, and then send the data off to the in-cab display and the cloud for further processing and other functions of the program. The team has created a bespoke cost-effective solution to datalogging as the path forward. Data has been collected, processed, and sent to the cloud from a demonstrator truck driving on public roads with the in-house solution.

The cloud infrastructure for the program has been developed and set up in Microsoft Azure by Esri. An overview of the cloud infrastructure can be seen in Figure II.1.3.3.

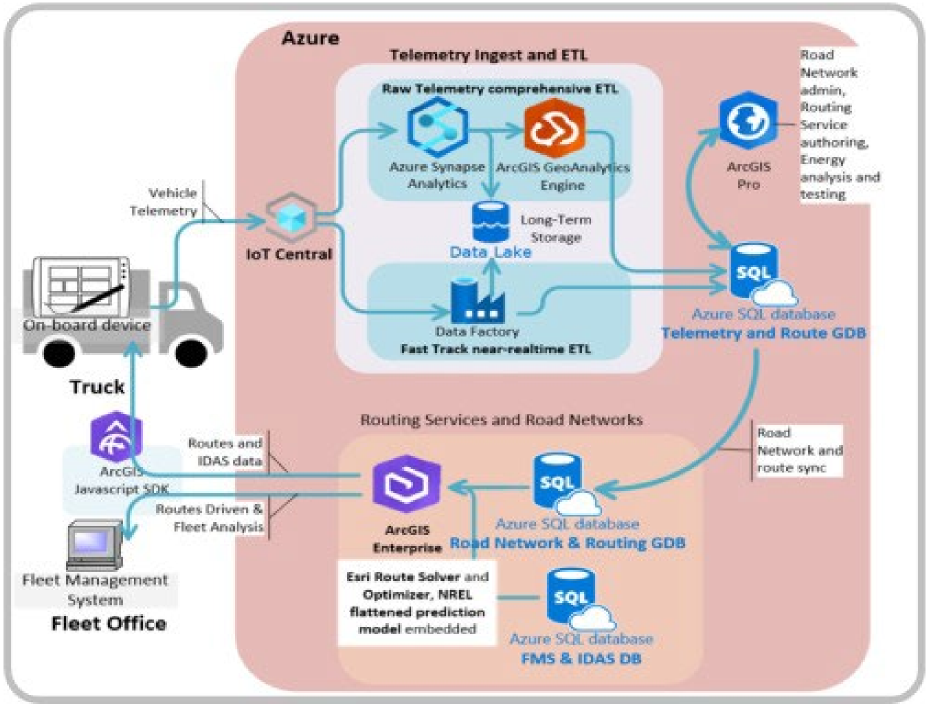


Figure II.1.3.3 CoVaR cloud architecture developed by Esri

The cloud infrastructure is currently set up and operational, with the ability to receive real-time data from the demonstrator truck and fleet partner vehicles. Work on the extract, transform, and load functionality to refine the process for speed and to supply necessary information for project partners has been ongoing.

Eco-Routing

The Eco-Routing portion of the project has made significant progress. NREL's RouteE powertrain tool has been trained on real-world PACCAR vehicle data to accurately predict the energy consumption of a possible route using a Random Forest algorithm. The results from the Random Forest algorithm were flattened into lookup tables and embedded in the routing algorithm to significantly speed up route selection of the pareto optimal route. The optimal route may not be the shortest distance or least time but will be the best tradeoff between the two based on the project's findings. This service will be integrated with Esri's ArcGIS tool to provide turn-by-turn directions on the in-cab display. An example of the eco-routing function can be seen below in Figure II.1.3.4.

Figure II.1.3.4 Example of Eco-Routing used in CoVaR

Eco-Driving

The eco-diving portion of the project has progressed through requirement definition, human centered design workshops, to initial wireframes and designs. Through several workshops and interactions, the team was able to determine that the optimal time for driver coaching is pre- and post-trip (Figure II.1.3.5). Live driver coaching offers potential benefit in being real-time but could potentially cause distractions or annoyance to the driver and is therefore not recommended. The driver coaching tool will analyze the driver's performance of the most recent trip and provide a screen with key details and metrics to help the driver understand where they could be more energy efficient.

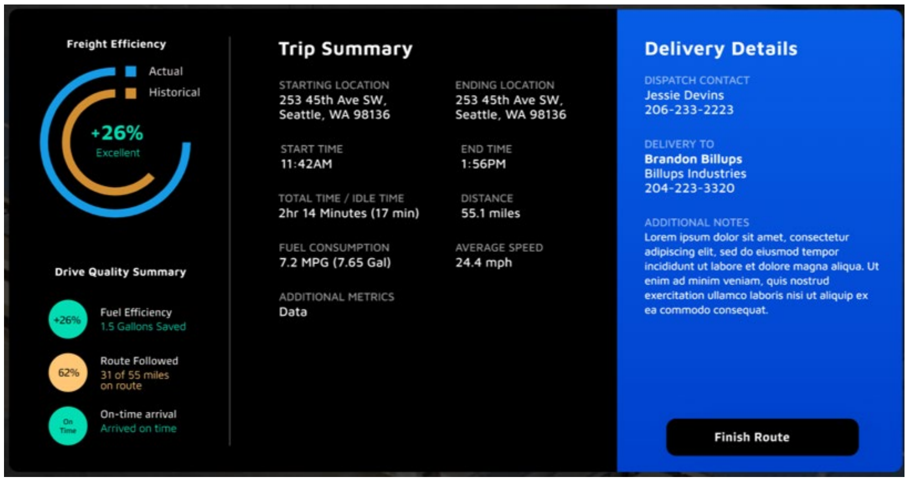


Figure II.1.3.5 Example of possible post-trip driver coaching metrics

Fleet Management Dashboard

The fleet management dashboard portion of the project has made significant progress. The team initially defined requirements and key metrics for the dashboard based on perceived fleet needs. The dashboard is a real-time cloud-based service to keep a fleet manager informed of performance and operation metrics related to their fleet (Figure II.1.3.6). This will help identify opportunities to reduce deadheading and gain fleet freight efficiency by monitoring the performance and use of the fleet. As we coordinate with our fleet partner, we will work to integrate their feedback and tailor the fleet management dashboard to their needs.

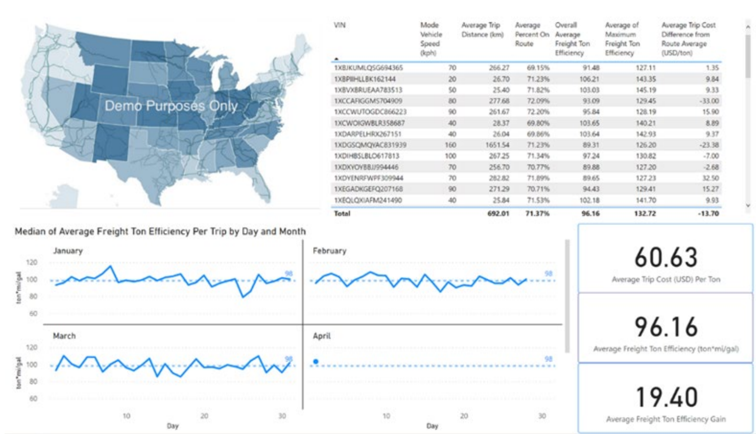


Figure II.1.3.6 Fleet management dashboard framework

Powertrain Configuration Optimization

The powertrain configuration optimization tool has been developed and machine learning models were trained to predict energy consumption to recommend a pareto-optimal powertrain to a fleet based on performance requirements and drive cycle data input by the user (Figure II.1.3.7). The tool can optimize and provide a trade-off relationship for energy efficiency, engine performance, selling cost, and more. The tool is designed to be agnostic to powertrain type (ICE or BEVs). The team has completed the application in MATLAB and is continuing to train the machine learning models to improve accuracy of the results.

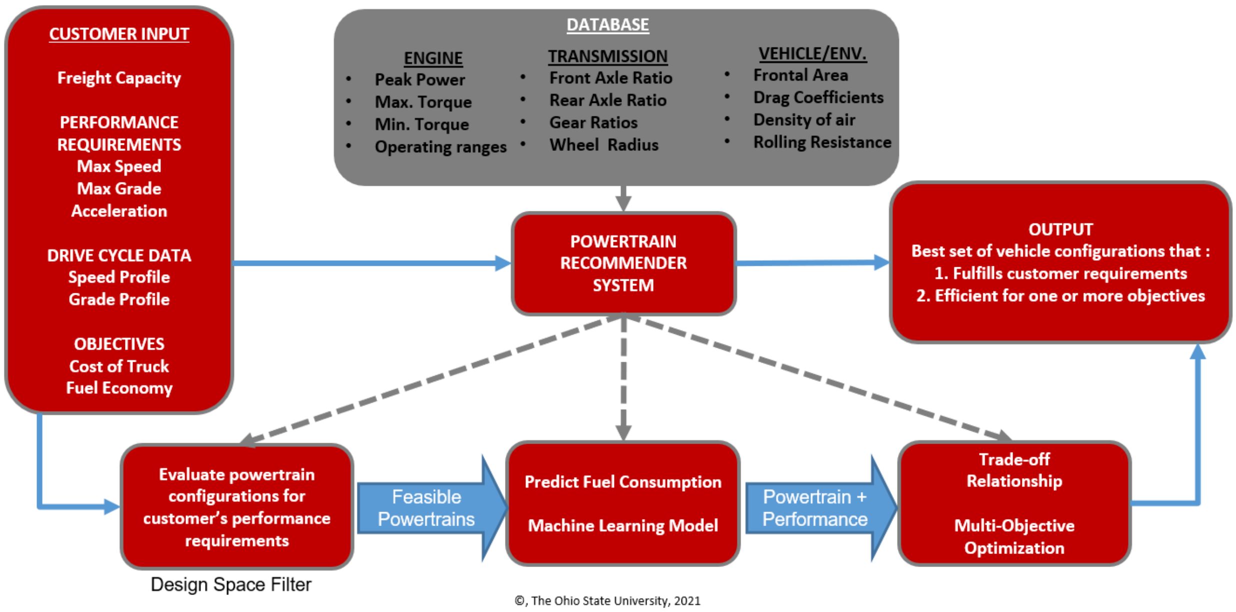


Figure II.1.3.7 Framework for the PRS

Conclusions

Over the project, the team has made significant progress on the development of the key connectivity and vehicle analytics technologies in the CoVaR offering. This effort has culminated in a working proof of concept demonstration truck that is operating at the PACCAR Technical Center and the local surrounding area. The demonstration truck includes an internally developed vehicle data aggregation unit, intelligent driver assistance system with turn-by-turn routing and driver coaching metric test displays, and the ability to send data to the cloud. These units are deployed in our partner fleet vehicles to record drive cycle data and allow the customers to use the routing technology to improve energy efficiency. The team also completed the powertrain recommender system tool to select the optimal powertrain configuration based on the customers drive cycle. Until the end of the project, the team will work to assess the potential and real-world impact of these technologies on freight efficiency improvements, with an overall goal of improving by 25%.

Acknowledgements

Kimberly Nuhfer, Project Manager, DOE

II.1.4 Connected and Learning Based Optimal Freight Management for Efficiency (Cummins Inc.)

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Start Date: October 1, 2020 End Date: December 31, 2023
Project Funding: $2,877,151 DOE share: $1,700,000 Non-DOE share: $1,177,151

Project Introduction

More than 25 billion tons of freight per year will be moved on the U.S. transportation system by 2045, representing a 40% increase over 2015 freight shipments, and over 65% of this tonnage will be transported by trucks [1], [2]. Part of this growth is due to e-commerce business demand that anticipates more than 40% growth in U.S. between years 2020 and 2024. Without fundamental changes in how goods are shipped, this could result in a significant increase in the energy consumption and GHG emissions. Emerging technologies from advanced powertrain systems such as electric, fuel cell, and advanced combustion engines along with connectivity and automated vehicle solutions are being developed for the vehicle efficient operation. Integration of trucks with these advanced powertrains and connected and automated technologies into the freight operation system, which is currently subject to fleet manager decisions and is operated without consideration of the powertrain specifications and the impact of real-world driving conditions on the powertrain performance and vehicle automation, could reduce the effectiveness of these advanced technologies to improve the freight operation efficiency.

In this project, Cummins, with a team of researchers, engineers, and end users from Venture Transport fleet company, ANL, University of California, Berkeley, and Michelin North America develop optimization and learning algorithms to solve the complex decision-making problem of the future freight management system with maximization of the efficiency of the system consisting of advanced powertrains, connectivity, and vehicle automation technologies.

Objectives

The objective of the project is to develop, implement, and validate a learning-based automated and optimal fleet management system that is used to demonstrate freight operation system efficiency improvement of 20%, or more, over a baseline fleet system.

Approach

The objective of the project is achieved by the development and validation of the proposed technology in three phases:

- **Phase 1 – Technology Development (2021) – Completed:** A freight system simulation is developed in POLARIS, including vehicle and powertrain models, models for connected and automated technologies, deep learning and optimization algorithms, and fleet management software inputs. The freight operation is characterized, and the baseline freight operation is verified in simulation. The path to target is refined for optimal freight operational efficiency.

- **Phase 2 – Technology Implementation and Demonstration in Simulation (2022) – Completed:** The learning and optimization algorithms are integrated with the POLARIS freight simulation models and the baseline fleet operation. The freight operation scenarios are defined. A ≥20% freight operation efficiency is demonstrated in simulation and the specific conditions where this improvement is possible is detailed. The significance or impact on fuel savings of the various levers is determined: advanced powertrain technologies and matching with trip specific requirements, connectivity and automation, and tire connectivity. Finally, path to target for freight operation optimal efficiency is refined with different levels of technology penetration.

- **Phase 3 – Technology Validation on Fleet (2023) – Ongoing:** Evaluation with fleet data is completed. The utilization and refinement of algorithms and digital models, and the energy and CO_2 savings validation on fleet are completed. The final steps will be data sharing, refinement and report the path to target for freight optimal efficiency, roadmap for freight operation efficiency with advanced powertrain, connectivity and automation emerging technologies, technology to market plan and TCO analysis.

Results

To manage the complex decision making of the emerging heterogonous fleets and make the path toward low emission freight transportation efficient and resilient, an AI-assisted fleet optimizer is developed to optimize decisions in terms of both investment in emerging technologies and efficient and reliable utilization of these technologies in the daily operation of the fleet as shown in Figure II.1.4.1. The optimization is done with respect to total cost of ownership including operation cost and subject to GHG emissions reduction target, fleet operation constraints, regulatory requirements, and cargo shipments demand. Learning algorithms are integrated to utilize operation data of the fleet and update models and decisions over time as new data is collected. This model is refined and updated with actual fleet operation data.

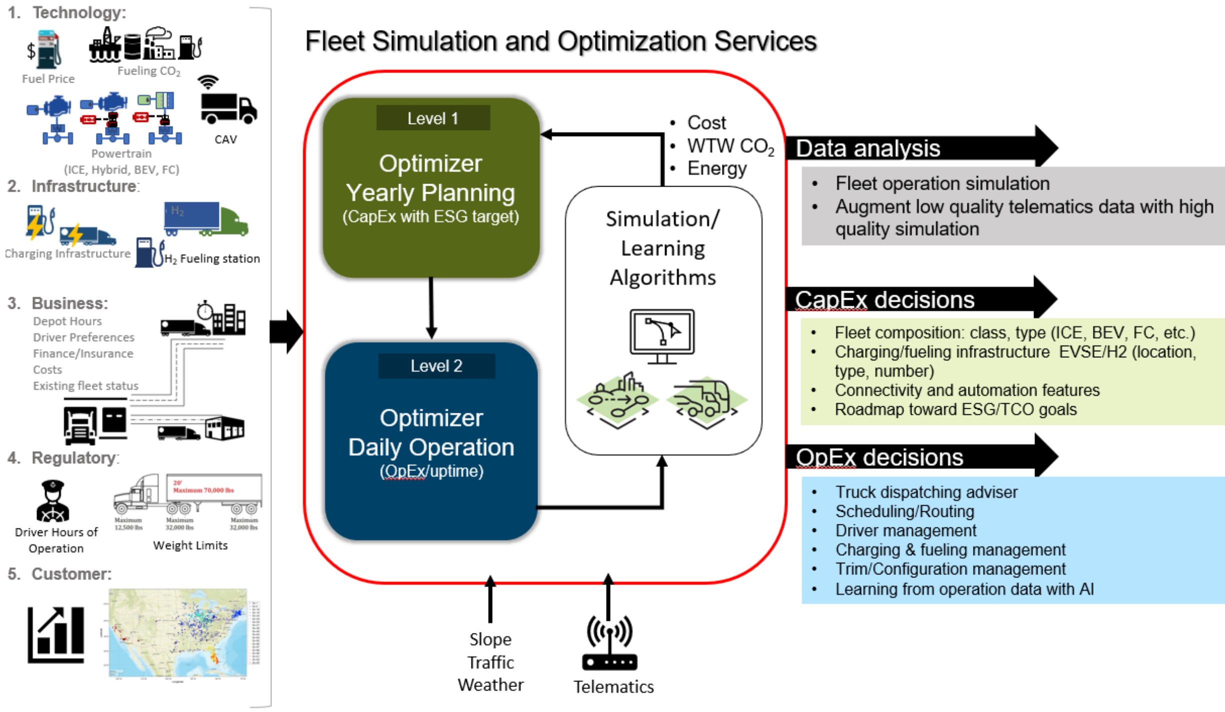

Figure II.1.4.1 Fleet optimizer framework

To demonstrate the target, the developed fleet optimization framework is applied on the baseline fleet with the optimized fleet composition shown in Table II.1.4.1.

Table II.1.4.1: Planning optimizer recommendations for the selected fleet

	Baseline	Optimized Fleet Composition
Fleet Composition (all trucks Class 8 regional haul)	10 conventional diesel	7 diesel ICE with ADAS 2 BEV with ADAS 1 BEV without ADAS All trucks with LRR tires Electric charger at depot (350 kW)

The fleet operation is simulated over 3 months (90 days) of baseline fleet with both the current all diesel conventional truck fleet composition and the optimized fleet composition. Through collaboration with Argonne National Laboratory team, the 3 months of operation is confirmed to be representative for 1 year of the fleet operation as shown in Figure II.1.4.2. Through collaboration with Michelin company, tire models for both standard and low rolling resistance (LRR) designs are developed, and the models are integrated in the vehicle models developed in Amber Autonomie tool. A dynamic tire model to capture the impact of tire pressure, ambient temperature and truck duty cycle is developed by Michelin company through testing tires under different operating conditions. The daily optimizer makes the decisions of the number and types of trucks dispatched, the payload on each trip, the schedule of the trips to be assigned to each truck, and the BEV recharge events and time. Figure II.1.4-3 shows the routing dispatch for one of the days of the 3 months of the fleet operation. By running the simulation over the 3 months of fleet operation, the results shown in Figure II.1.4.4 to Figure II.1.4.7 are achieved. As it is demonstrated, the demand and consequently the vehicle miles travelled, energy consumption and emissions are varying in each day. More than 20% cumulative improvement in fleet level well-to-wheels (WTW) GHG CO_2 emissions is achieved with the recommended fleet composition and operation optimization.

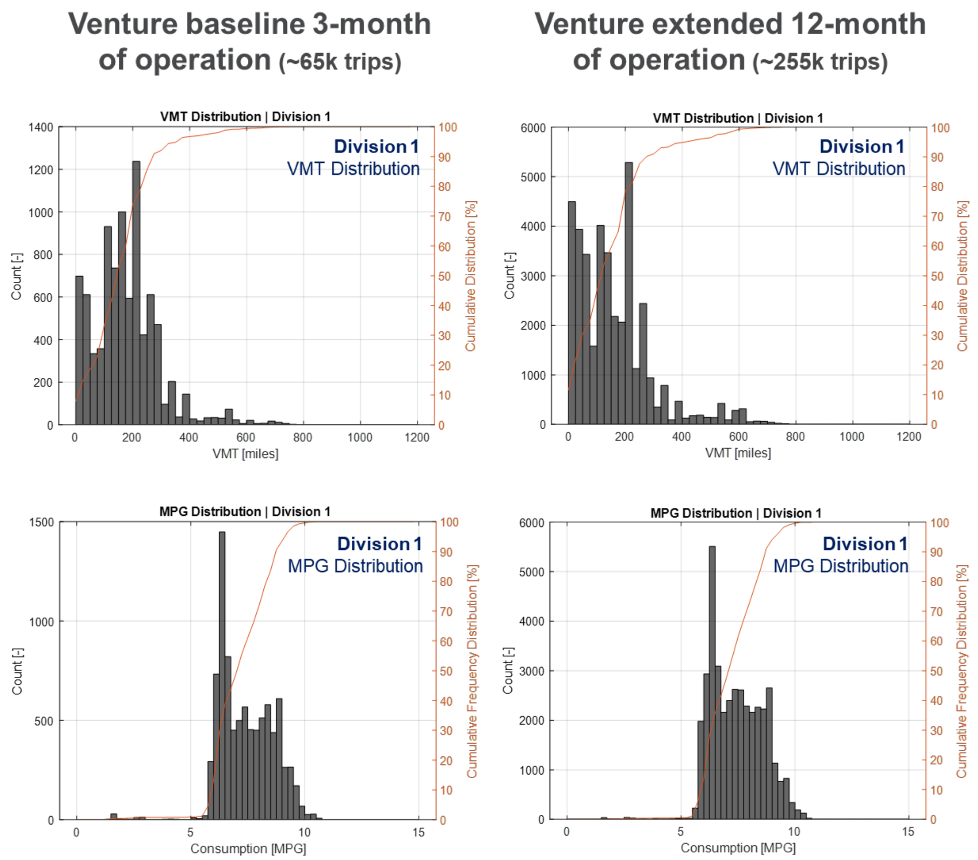

Figure II.1.4.2 Comparison of selected 3 months of fleet operation versus 1 year of operation

Figure II.1.4.3 Daily optimizer routing schedule on one of the days of the 3 months of operation

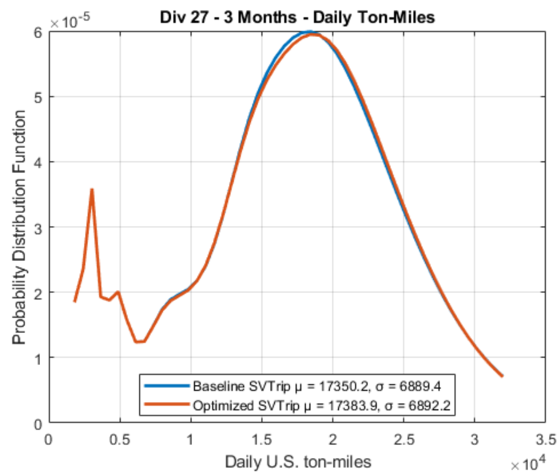

Figure II.1.4.4 Distribution of daily ton-mile

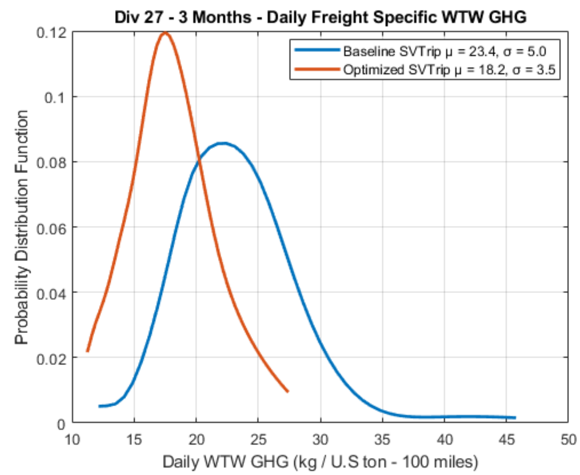

Figure II.1.4.5 Distribution of freight specific WTW GHG emissions

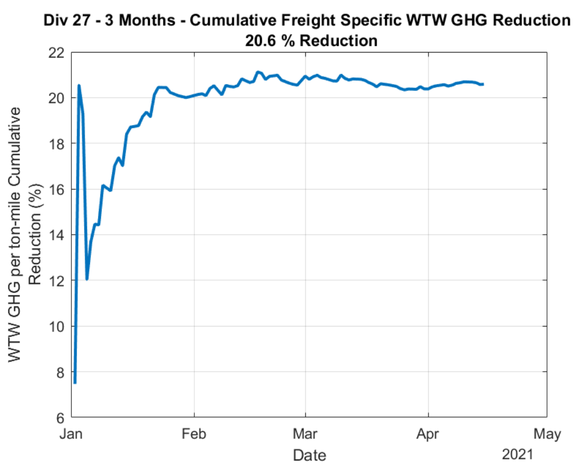

Figure II.1.4.6 Cumulative freight specific WTW GHG reduction

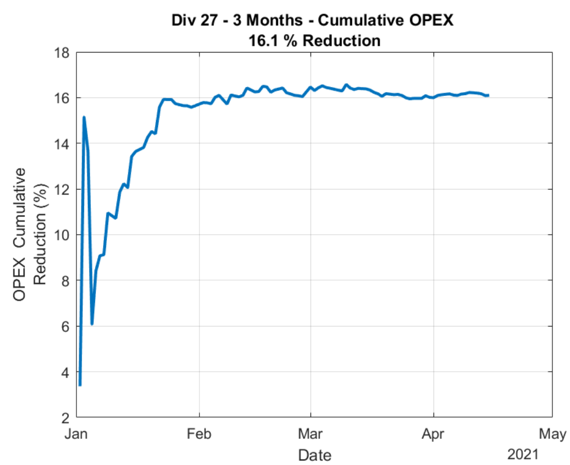

Figure II.1.4.7 Cumulative operational expense (OPEX) reduction

To assess the sensitivity of the results to EV range variations due to operation at unfavorable weather conditions including low ambient temperature, 2 case studies are conducted. In these case studies, the average energy consumption in kWh/mile is increased by 10% and 20%, respectively. The results are summarized in Table II.1.4.2. As shown, the efficiency is reduced as more diesel trucks are required to be dispatched due to EV range reduction. EV range variation is a challenge and could even lead to failed trip dispatching. The adjusted value in the table is due to a few failed trips observed. The failed trips are replaced with a diesel truck to make freight shipments similar across different conditions.

Table II.1.4.2 Sensitivity of the results to EV range variations

% Change in average kWh/mile electricity energy consumption	0% (nominal)	10% (cold)	20% (very cold)
Adjusted WTW CO2 Efficiency (%)	20.13%	17.66%	12.13%
Adjusted OPEX (%)	16.84%	15.33%	12.78%

To further improve dispatching and avoiding failed trips, learning algorithms are developed through collaboration with the University of California, Berkeley. As shown in Figure II.1.4.8, the learning algorithms for daily operation optimization leads to reliable deployment of electric trucks with different sets of duty cycles.

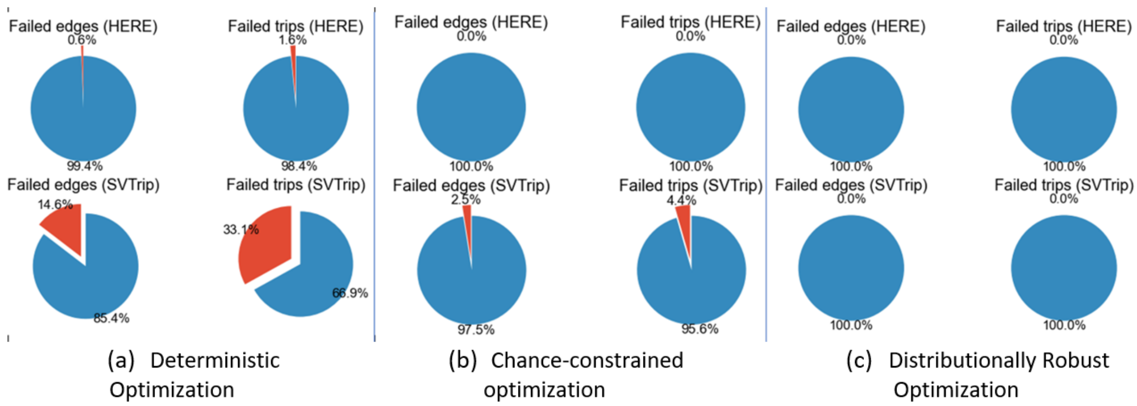

Figure II.1.4.8 Percentage of trip failures and edge failures for the (a) deterministic optimizer, (b) chance-constrained optimizer and (c) distributionally robust optimizer

Conclusions

The heterogenous fleet is emerging as decarbonization technologies are deployed by fleets towards lowering the freight operation emissions in medium- and heavy-duty vehicles. To make the path towards low emission freight transportation efficient and resilient, an AI-assisted fleet optimizer is developed in this project to help fleet managers in making optimized decisions for efficiency and cost. The fleet management optimizer is also integrated with a model of the fleet from POLARIS-SVTrip-Autonomie to simulate the operation of the fleet over a given time indicated the significance of day-to-day variations on emissions and energy consumption of a freight transportation fleet. The fleet optimizer is integrated with baseline fleet simulation models and both baseline and optimized fleet simulation results over 3 months of operation are reported. The models are further refined with real fleet operation data and updated vehicle specifications and optimization algorithms. This framework is used to demonstrate ≥20% improvement in freight efficiency in terms of WTW CO_2 GHG emissions per U.S. ton-mile of cargo shipments while all fleet operation constraints are enforced, and the cost is minimized. The developed models and methods can be applied to different fleets and under different cost and technology readiness scenarios.

Key Publications

1. Ruiting Wang, Patrick Keyantuo, Teng Zeng, Jairo Sandoval, Aashrith Vishwanath, Hoseinali Borhan, Scott Moura, "Optimal Dispatch and Routing of Electrified Heavy-Duty Truck Fleets: A Case Study with Fleet Data", 2023 American Control Conference (ACC), San Diego, CA, USA, 2023, pp. 1729-1734

2. Patrick Keyantuo, Ruiting Wang, Teng Zeng, Jairo Sandoval, Aashrith Vishwanath, Hoseinali Borhan, Scott Moura, "Distributionally Robust and Data-Driven Solutions to Commercial Vehicle Routing Problems", Accepted, IFAC World Congress, 2023

3. Ruiting Wang, Patrick Keyantuo, Teng Zeng, Jairo Sandoval, Aashrith Vishwanath, Hoseinali Borhan, Scott Moura, "Optimal Routing of a Mixed Fleet of Heavy-Duty Trucks with Pickup and Delivery: A Case Study with Fleet Data", Under Review, IEEE Transactions on Intelligent Transportation Systems, 2023.

References

1. U.S. DOT Federal Highway Administration

2. U.S. E-Commerce Sales Forecast. statista.com

II.1.5 Developing an Energy-Conscious Traffic Signal Control System for Optimized Fuel Consumption in Connected Vehicle Environments (University of Tennessee at Chattanooga)

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Start Date: October 1, 2020 End Date: June 30, 2024
Project Funding: $2,404,469 DOE share: $1,893,168 Non-DOE share: $511,301

Project Introduction

This project aims to address the energy related challenges associated with adaptive traffic control systems by integrating CVs and connected infrastructure (CI). Specifically, we propose to develop a CV-based adaptive traffic control system that aims to improve fuel consumption in mixed traffic environments (CVs and unconnected vehicles) along a corridor through capitalizing on emerging CV and CI communication technologies, as well as opportunities created by recent advances in AI, optimization, and edge computing. The system will be implemented in the MLK Smart Corridor, the urban testbed managed by the University of Tennessee at Chattanooga (UTC) and the City of Chattanooga.

In 2018, the transportation sector alone accounted for more than 69% of the U.S. petroleum consumption and more than 37% of the U.S. CO_2 emissions [1]. Since stop-and-go conditions contribute significantly to those numbers, addressing congestion in an energy-efficient way would have a major environmental impact. The critical role of traffic signals in network congestion was highlighted in the 2012 National Traffic Signal Report Card, with signals causing 295 million vehicle hours of traffic delay on major roads and accounting for 5% to 10% of all traffic related delay. Unfortunately, the grade given to the national state of traffic signals was a D+, indicating the major impact the traffic signal system has on congestion and the environment. Past research in ATCS has been directed to improve these impacts through objective functions that primarily aim to reduce delays and improve travel time [2]. While often a tertiary objective, to our knowledge, there is limited research that targets minimizing fuel consumption as the main objective for an implemented ATCS [3]. Additionally, attempts to model fuel consumption are often based on fleet mix and driving cycle assumptions and simplifications that reduce the effectiveness of such systems. In fact, ATCS should meet the needs of the real-time heterogeneous modes (vehicles, pedestrians, transit, emergency vehicles, etc.). *Our vision is to address these challenges by integrating CV and CI to enable real-time monitoring of system dynamics and applying artificial intelligence and game theory focused on minimizing fuel consumption and emissions*. Optimizing these objectives is a complex problem requiring comprehensive and dynamic data from multiple sources, as well as real-time scalable optimization algorithms. During the past two years, we have designed and implemented data-driven algorithms, digital twin of the testbed, and validated our algorithms in the digital twin. In the coming year, we plan to implement and test it along the MLK Smart Corridor in downtown Chattanooga.

Objectives

- Develop energy-efficient signal control algorithms that capitalize on wireless communications and emerging data sources.

- Develop a multi-modal priority system that can deal with simultaneous priority requests from various modes in an energy-efficient fashion.
- Comparatively evaluate various modes of communication for the proposed technology in terms of latency and packet losses.
- Demonstrate capabilities and evaluate the portability of the proposed technology through high-fidelity simulation and field testing.

Approach

- Build a data infrastructure to ingest, store, and analyze historical/real-time data from different sources.
- Develop a performance measure that characterizes impact of signal timings on excessive fuel consumption and vehicular emissions.
- Develop high accuracy AI-based traffic state prediction models at intersections.
- Develop machine-learning and game-theory based optimization algorithms for fuel consumption and vehicular emissions.
- Build the MLK Smart Corridor digital twin to capture the interactions between different components of the Eco-ATCS.
- Validate the developed algorithms using advanced simulation & modeling techniques.
- Demonstrate the developed technologies and algorithms through field testing.

Results

The focus of the third year has been on testing our proposed Eco-ATCS on the field. To achieve that we modified our data resources to mitigate the existing 1-minute delay, enhanced our data integration, updated Eco-PI to include multiple vehicle types, transitioned from HIL to SIL, fine-tuned our proposed RL-based Eco-ATCS to include pedestrian and bus, and performed several rounds of testing in the field.

Deep Learning-Based Framework for Per-Lane Vehicles Counting Using GRID-SMART Data

GRID-SMART cameras (GridSmart) have been one of the sources of data from the field. This data is aggregated and available at every one-minute interval. To enable our Eco-ATCS perform in real time, we developed a deep learning-based framework for per-lane vehicle counts using GridSmart data. The framework was developed based on YOLOv7 and has been carefully designed and implemented to efficiently process and analyze traffic data. Figure II.1.5.1 illustrates the overall pipeline of the system.

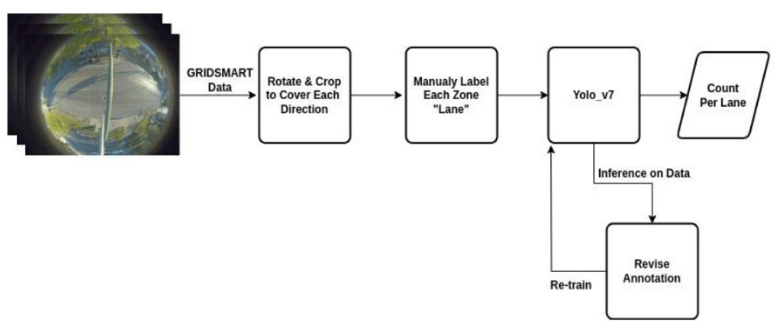

Figure II.1.5.1 System pipeline

The system was trained with comprehensive data which was meticulously annotated using the CVAT annotation tool. The team manually annotated a total of 3,200 images to facilitate the training process. The final training results are shown in Figure II.1.5.2. The overall performance is summarized as follows:

- 80.56% = bus AP || Score threshold = 0.5 : F1 = 0.73 ; Recall = 66.67% ; Precision = 80.00%
- 96.53% = car AP || Score threshold = 0.5 : F1 = 0.94 ; Recall = 94.35% ; Precision = 94.28%
- 81.27% = truck AP || Score threshold = 0.5 : F1 = 0.85 ; Recall = 78.57% ; Precision = 91.67%
- mAP = 86.12%

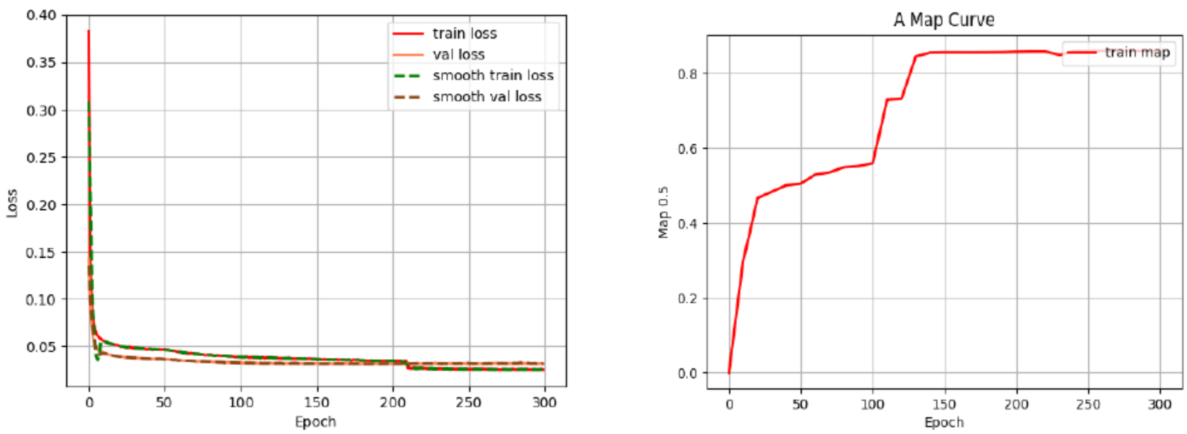

Figure II.1.5.2 Training results of our proposed per-vehicle count algorithm

Development of Eco-PI for various vehicle types

The stop penalty needed to reduce fuel consumption (FC) is derived based on the fuel consumed during the three driving modes of a complete stop at signalized intersections. These modes are deceleration, idling, and acceleration. An example of field vehicular trajectory of those modes is shown in Figure II.1.5.3a. The change in speed during those modes can be represented by a cruising speed stop profile (CSSP), as displayed in Figure II.1.5.3b. Cruising speeds before deceleration and after acceleration are not necessarily equal. In fact, field data processing, discussed later, showed that it is rare that a vehicle decelerates from a particular cruising speed and accelerates back to the exact original speed. The reality is that the cruising speed after accelerating can be lower or higher than the original cruising speed before stopping. Figure II.1.5.3c depicts changes in acceleration during a stop event. Finally, the instantaneous FC changes over time during a CSSP are demonstrated in Figure II.1.5.3d.

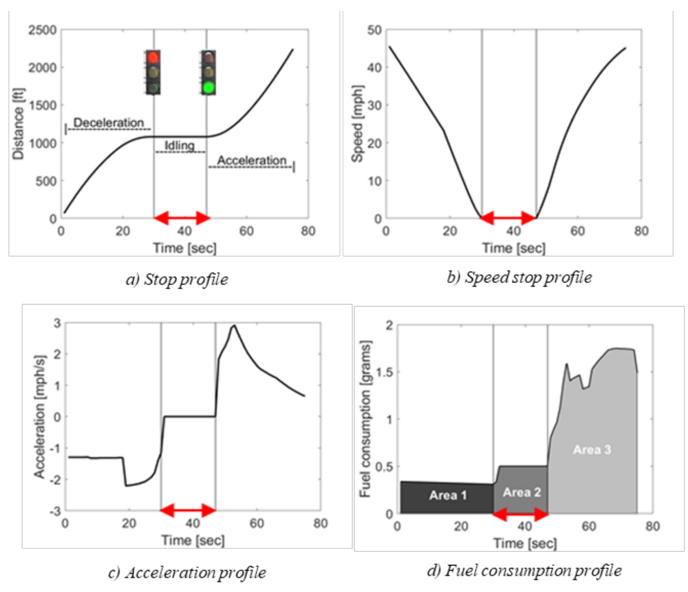

Figure II.1.5.3 Dynamics and kinematics of a stopped vehicle

To account for different types of vehicles stop penalty (k) is defined as function of following parameters:

$$K = f(S_A, S_D, G_A, FC_I, T_D, A)$$

S_A : accelerating (final) speed (mph)

S_D : decelerating (initial) speed (mph)

G_A : accelerating grade (%)

FC_I : idling fuel consumption rate (g/s)

T_D : decelerating duration (s)

A : acceleration (ft/s^2)

After multigene genetic programming model training following equations for k stop penalty of LDVs and buses/heavy-duty vehicles (HDVs) were obtained:

$$k_{LDV} = \frac{1.321e-2 \cdot {S_D}^2 \cdot T_D + 0.3979 \cdot {T_D}^2 - 5.102 \cdot FC_I \cdot T_D}{FC_I \cdot T_D} +$$

$$\frac{1.608 \cdot S_D + 0.2311 \cdot S_D \cdot T_D + 4.966e-3 \cdot {S_D}^2 \cdot G_A \cdot T_D + 3.073e-2 \cdot {S_D}^2 \cdot FC_I \cdot T_D + 7.796e-3 \cdot S_A \cdot S_D \cdot T_D}{FC_I \cdot T_D \cdot A}$$

$$k_{bus/HDV} = 6 \cdot (\frac{8.674\,e-19 \cdot S_D \cdot (1.574\,e14 \cdot S_A \cdot {G_A}^2 + 1.574\,e14 \cdot S_A \cdot S_D \cdot G_A + 7.553\,e17)}{FC_I \cdot A} -$$

$$\frac{(8.314\,e-3 \cdot {S_D}^2 \cdot {FC_I}^2 \cdot {T_D}^2 + 8.977 \cdot {S_D}^2 \cdot FC_I + 5.725\,e23 \cdot {FC_I}^2 + 2.983 \cdot (S_A \cdot FC_I \cdot T_D) + 4.946 \cdot T_D) \cdot 1.694\,e-3}{FC_I^2}$$

It is worth mentioning that if the fleet consists of both categories (LDVs and buses [HDVs]) final K for the movement should be adjusted by the percentage of each vehicle category in the fleet:

$$K = (1-p)k_{LDV} + p \cdot k_{bus/\,HDV}$$

Finally, it is important to remember that the Eco-PI is a combination of mobility and sustainable measures to be minimized during the optimization, which can be mathematically expressed as:

$$Eco-PI_{total}^{i} = \sum_{m=1}^{n} D_{m_i} + K_{m_i} * S_{m_i}$$

i: Observed intersection

n: Total number of eligible movements

m: An eligible movement in the network

D: Stopped delay for movement

K: Stop penalty of the fleet

S: Number of stops

Eco-PI considers the impact of several operating conditions (e.g., vehicle type, speed, grade) that impact vehicular fuel consumption footprints at signalized intersections.

Software-in-the-loop simulation

In addition to HIL testing in the CAVE lab that was reported in the previous annual report, to test the actual impact on energy/fuel consumption, the team conducted HIL testing using the actual controller device that was connected to the same internet network as the computer, which runs Vissim. We did this testing on couple of devices, one at the University of Pittsburgh (Pitt) and one at UTC. In preparation for our field testing, we needed to test our Eco-ATCS on multiple intersections. HIL simulations require additional routers to create subnetworks. Additionally, even though connecting more than one actual controller to a computer is theoretically possible, SIL simulations are more convenient for cases requiring more than one controller (e.g., MLK corridor). For example, an experiment with 11 controllers can be possible with HIL and SIL simulations, but the reasonable option is SIL simulation. There are two main reasons for this selection. First, the subnetwork of 10 controllers (or less) requires an advanced router having the necessary number of ports. Second, placing additional actual controllers demands more space and time. For SIL simulations, the computer running Vissim also runs the controller's software. Therefore, an additional piece of hardware, such as a router, is not needed. The controller hardware has software running the main logic of traffic control system. It is worth noting that the same type of connection protocol is used for HIL and SIL simulations. Furthermore, all traffic signal controller manufacturers use the National Transportation Communications for Intelligent Transportation System Protocol (NTCIP), which is a communication protocol. Thus, before implementing Eco-ATCS to the field we tested them in SILS environment since in SILS environment we can test all 11 intersections whereas in HILS we can test up to 2 intersections.

We connected all 11 intersections on MLK corridor in Vissim to SEPAC m60 controllers. For each controller, port numbers are assigned, and necessary files are created. First, 11 virtual controllers were connected with defaults signal timing plans to verify the established connection. Once the connection was established through assigned port numbers. Our team used software called TACTICS to upload field signal timing plans for all 11 intersections from the MLK corridor. In Figure Figure II.1.5.4, one can see all 11 virtual machines representing field controllers working with the help of the management system of SEPAC TACTICS.

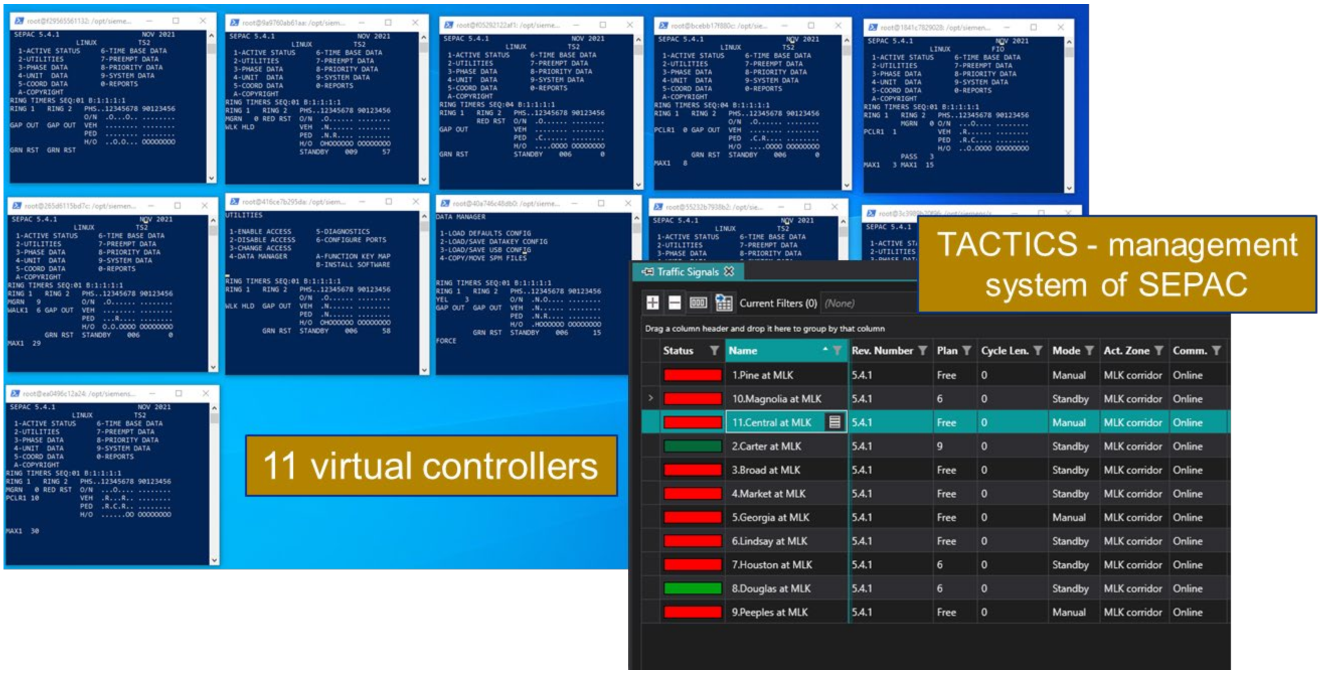

Figure II.1.5.4 View of Siemens SEPAC SILS

In Figure II.1.5.5, the signal status is the same in both platforms meaning that the communication is established properly. In addition, the eastbound approach has two vehicles placing a call and that vehicle call can also be observed in TACTICS.

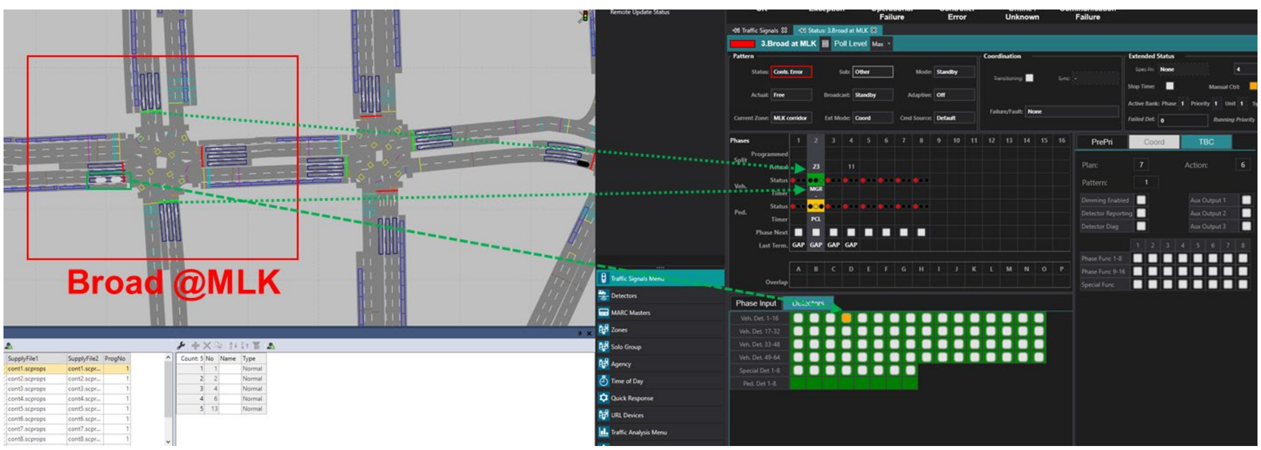

Figure II.1.5.5 Field signal timing plans operating in SILS environment at Broad @MLK

Before field deployment of Eco-ATCS, it is necessary to ensure that all the constraints are met and that the Eco-ATCS performs as expected. Having developed a fully operating SILS environment, the Pitt team started exploring the possibilities of implementing Eco-ATCS to field controllers. First, Pitt identified three ways of implementing various optimization logics to the actual field controller:

1. Changing time-of-day plans
2. Manipulation of vehicle calls
3. Using holds, omits and force-off.

The first approach had several unfavorable aspects, including its high memory requirement and limited flexibility compared to the other two approaches. As a result, it was determined that the first approach is unsuitable for implementation. To implement Eco-ATCS, or in other words optimization output, to an actual controller NTCIP software must be used. Through NTCIP software NTCIP messages are sent to controller in form of hold/omit/force offs or “manipulated’ detection calls. The controller then relays the phase status back to the NTCIP software, which converts it to a .json file and transmits it back to the Vissim microsimulation environment. It is worth noting that once Eco-ATCS is deployed in the field, there will be no messages sent back to the Vissim digital twin.

In Figure II.1.5.6, framework for offline Eco-ATCS implementation is explained. First, the output from UTC server is obtained in the form of text file. DGMARL output is then converted to a file readable to NTCIP in data reader module. The converted output contains second by second phase statuses. As such, information from text file is sent to the main NTCIP module and then in form of NTCIP message it is sent to SEPAC m60. It is important to note that, in this offline implementation, the SEPAC m60 receives detection output from Vissim, while Vissim receives signal status directly from the SEPAC m60 (which is provided by the DGMARL output). Additionally, the NTCIP software acts as a mediator between Vissim and the SEPAC m60 by transmitting messages that are readable to both Vissim (.json files) and the SEPAC m60 (NTCIP messages).

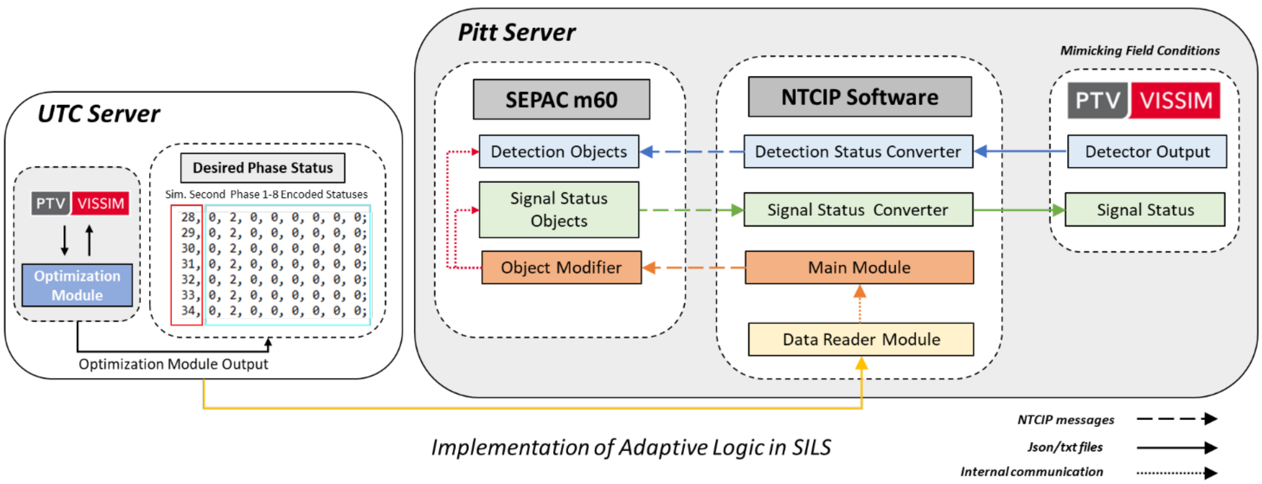

Figure II.1.5.6 Framework for offline adaptive logic implementation

Fine-tuning the Proposed Global Optimization Algorithm

The performance of the proposed global optimization algorithms was enhanced by enabling a phase sequence free mode. This allowed the decentralized graph-based multi-agent reinforcement learning (DGMARL) model to switch to the phase with the highest traffic occupancy. To achieve this, the team updated the input and output of the DGMARL model. Our team performed multiple tests to validate the results, including 1-hour simulation and 3-hour simulations, to demonstrate how both the overall Eco-PI improved and how the overall stop delays and number of stops reduced.

- 1-hour simulation:
  - Overall Eco-PI improved by 16.63%
  - Overall stop delay improved by 43.80%
  - Number of stops reduced by 15.13%
- 3-hour simulation:

- Overall Eco-PI improved by 15.29%
- Overall stop delay improved by 43.96%
- Number of stops reduced by 10.05%

Our team also improved the DGMARL execution time by implementing multi-threading techniques and enhanced the execution time of the Actuated COM solution for observing Eco-PI by utilizing multi-threading techniques. The improvement is shown in Table II.1.5.1

Table II.1.5.1 Improved DGMARL Execution Time

Model	Simulation Hour(s)	Original Timing	Improved Timing	Output(s)
Actuated	1 hour	2 hrs., 34 min.	23 min., 59 sec.	Eco-PI, Vehicles in Net, Signal State
	3 hours	Around 5 hrs.	1 hr., 4 min.	
DGMARL	1 hour	3 hrs., 38 min.	1 hr., 36 min.	Eco-PI, Vehicles in Net, Signal State, Node State, and other details
	3 hours	Around 12 hrs.	4 hrs., 55 min.	

The team also integrated LDVs and HDVs formulas in Eco-PI and then trained DGMARL.

Data Integrations for Field Testing

We have enhanced our data integration in preparation for the field test:

- Developing an interface to connect and read field inputs, specifically SPaT data, and vehicle arrival information
    - SPaT data is retrieved from GridSmart using a custom API developed by the CUIP data collection team. This API has been successfully integrated into DGMARL.
    - Vehicle arrivals are observed through Computer Vision, a custom API, developed by the data collection team, and sends observed vehicle count per lane to DGMARL.
- While the Vissim Simulator provided vehicle occupancy, field testing only provides vehicle counts. Therefore, DGMARL has been updated with custom logic to estimate vehicle occupancy based on vehicle arrival patterns.
- DGMARL has been untethered from Vissim and is not connected to the field's SPaT configuration (Field Testing Version), incorporating phase-specific parameters such as minimum green, yellow duration, red clearance, and pedestrian serving time (Walk + Flashing Don't Walk).
- To ensure accurate time measurements for green, yellow, and red clearance durations, DGMARL now uses the field controller's timestamp from the SPaT input. This allows for precise calculations of signal timings, even if DGMARL's execution time varies.

Pedestrian Push Button Request Handling

To enhance the absence of pedestrian push button requests in DGMARL, the model has been enhanced with the capability to handle pedestrian requests. The implementation process included:

- Analyzing input fields and values from GridSmart to understand pedestrian push button requests.
- Identifying “spatPedestrianCalls” as the field that indicates the phase number where a push button was pressed (i.e., “spatPedestrianCalls” = 2 corresponds to Phase 2).
- Updating DGMARL code to prioritize pedestrian push button requests over vehicle demand.
- Holding push button requests if they are for the current phase with an active green signal, ensuring that all phases receive a minimum green or pedestrian recall serving time.

Initial Delay and Synchronization with Controllers Signal Status

The team improved the DGMARL’s field testing code to synchronize with field controller signal status. This involves waiting for the ongoing current phase to complete before synchronizing DGMARL’s signal timing plan with the next phase.

Field Testing, Issues, and Fixes

Field testing and issue resolution were crucial steps in this quarter’s progress and includes:

- DGMARL was tested and aligned with NTCIP module expectations for signal status input.
- Integration testing was conducted for three modules: Computer Vision for vehicle observation, DGMARL, and NTCIP. This was successfully tested at the Peeples intersection in the MLK corridor.
- The LAB_M60 machine was employed for initial testing, which was set up with the Georgia Avenue intersection signal timing plans.
- During initial testing on the LAB_M60 machine, we noticed issues such as left phase servicing problems and red flashing lights. These issues were resolved by adjusting lane index configurations and improving NTCIP application code.
- After multiple trials on the LAB_M60 machine, we proceeded to test at real intersections. Initial tests were performed at Peeples intersection, where the team verified that signal timing synchronization worked well.
- Subsequently, we expanded the team’s testing to include multiple intersections, encompassing Peeples, Douglas, Houston, Georgia, Market, and Broad.
- The testing culminated in a successful demonstration on October 23, 2023, involving Lindsay, Georgia, and Broad intersections (Figure II.1.5.7). This demonstrated effective integration and control of real intersections, with minimum vehicle queues and efficient handling of pedestrian push button requests.

Communication Test

This test was conducted to ensure uninterrupted communication with the field controller. Upon executing the NTCIP software, the team achieved consistent data reception from the controller. This successful test outcome confirmed that the Eco-ATCS was effectively and reliably communicating with the field controller, a pivotal step in the system’s real-world deployment.

Detection Suppression Test

This test aimed to prevent the GridSmart system from initiating detection calls. Initially, the team intended to modify the dynamic value of the detection calls object through the NTCIP software, which would normally register as zero when no detection calls were present but would change when a detection call occurred, such as when a car was detected in a specific phase. However, the team encountered an obstacle in the form of the City of Chattanooga's SEPAC software version 5.2, which did not support this object. SEPAC 5.3 was used in the team's lab tests. Consequently, the GridSmart system was able to place calls during this field test, resulting in an unsuccessful outcome. For subsequent, the team manually disconnected GridSmart by adjusting the port settings of the controller.

Figure II.1.5.7 Performing several rounds of field test in September and October 2023

Conclusions

The achievements of our team during this annual reporting period underscore significant advancements in the field of traffic optimization and environmental sustainability. Q1 marked the development of the Eco-PI equation, integrating mobility and sustainability metrics for signalized intersections. The subsequent enhancement of the DGMARL model resulted in a remarkable 29.88% improvement in Eco-PI values during the PM peak period. Q2 showcased further improvements, including reduced execution times, integration of light-duty and heavy-duty vehicles in Eco-PI, and a thorough analysis of fuel consumption and emissions. The comprehensive evaluation of the DGMARL model revealed substantial benefits, with notable improvements in overall Eco-PI, stop delays, and the number of stops during both 1-hour and 3-hour simulations. The introduction of a deep learning-based framework for per-lane vehicle counts demonstrated the team's commitment to leveraging advanced technologies for traffic data analysis. The framework achieved impressive accuracy in detecting buses, cars, and trucks, contributing to a deeper understanding of traffic patterns. Furthermore, the team's dedication to real-world applicability was evident in successful hardware-in-the-loop integration with a physical vehicle, field testing of SPaT data integration, and ongoing efforts to enhance the realism of vehicle driving behavior in simulations. Finally, the team visited Chattanooga and performed a 2-day field testing. These tests were successful. We further hosted program and technical managers from DOE in October 2023 and performed additional field testing of Eco-ATCS over several intersections.

Key Publications

1. A. Gammaa, S. Khaleghian, T. Tran, M. Sartipi, "Improving Vanet Simulation Channel Model in an Urban Environment Calibration Using Real-World Communication Data," 102st Transportation Research Board Annual Meeting, January 2023.

2. I. Erdagi, N. Dobrota, S. Gavric, A. Stevanovic, "Cycle-by-cycle Delay Estimation at Signalized Intersections by using Machine Learning and Simulated Video Detection Data", IEEE Proceedings of 2023 8th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), 2023.

3. I. Erdagi, S. Gavric, A. Stevanovic, "Impact of Adaptive Traffic Control Implementation Methods on Operations of a Coordinated Network", 103rd TRB Meeting Presentation, Under Review in Transportation Research Record, 2023.

4. S. Gavric, N. Dobrota, I. Erdagi, A. Stevanovic, O. Osman, "Estimation of Arrivals on Green and Signalized Intersections Using Stop-bar Video Detection", Transportation Research Record, 2023.

5. Y. Hassan, J. Zhao, A. Harris, M. Sartipi, "Deep Learning-Based Framework for Traffic Estimation for the MLK Smart Corridor in Downtown Chattanooga, TN", 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), Bilbao, Spain.

6. Y. Hassan and M. Sartipi, "ChattSpeed: Toward a New Dataset for Single Camera Visual Speed Estimation for Urban Testbeds", 2023 IEEE International Conference on Big Data (Big Data), Sorrento, Italy.

7. Y. Hassan, J. Zhao, M. Sartipi, "Deep Learning-Based Multi-Vehicle Tracking with Speed Estimator Case Study: MLK Smart Corridor in Chattanooga, TN", 2022 6th Black in AI workshop at NeurIPS Conference, New Orleans, LA.

8. V.K. Kumarasamy, A.J. Saroj, Y. Liang, D. Wu, M. Hunter, A. Guin, M. Sartipi, "Traffic Signal Optimization by Integrating Reingrocement Learning and Digital Twins", IEEE Smart World Conference, Portsmouth, UK, Unpublished, August 2023.

9. T.T. Nguyen, H.H. Nguyen, M. Sartipi, M. Fisichella, "Multi-Vehicle Multi-Camera Tracking with Graph-Based Tracklet Features", IEEE Transactions on Multimedia, 2023.

10. T.T. Nguyen, H.H. Nguyen, M. Sartipi, M. Fisichella, "Real-Time Multi-Vehicle Multi-Camera Tracking with Graph-Based Tracklet Features". Transportation Research Record, 2023.

11. A.J. Saroj, M. Hunter, S. Roy, A. Guin. "A Three-Tier Incremental Approach for Development of Smart Corridor Digital Twins", 2023 IEEE 26th International Symposium on Real-Time Distributed Computing, 2023.

12. A.J. Saroj, S. Roy, A. Guin, M. Hunter, "Data Quality Assessment Process for Real-Time Data-Drive Traffic Microsimulation of Smart Corridor", National Academies, 103rd Transportation Research Board, Annual meeting, Poster session, Washington, D.C., Jan 7th-11th, 2024.

13. A.J. Saroj, S. Roy, A. Guin, M. Hunter, "Impact of Connected Corridor Volume Data Imputations on Digital Twin Performance Measures", International Journal of Transportation Science and Technology, 12 (2), 476–491, 2, 2023.

14. T. V. Tran and M. Sartipi, "Revisiting Pixel-based Traffic Signal Controls using Reinforcement Learning with World Models", The Workshop on Artificial Intelligence for Social Good at the 37th AAAI conference on artificial intelligence, February 2023.

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1. S. Davis and R. G. Boundy, "Transportation energy data book: Edition 38," tech. rep., Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States), 2020.

2. M. P. Hunter, S. K. Wu, H. K. Kim, and W. Suh, "A probe-vehicle-based evaluation of adaptive traffic signal control," *IEEE Transactions on Intelligent Transportation Systems*, 2012.

3. C. Sun, J. Guanetti, F. Borrelli, and S. Moura, "Optimal eco-driving control of connected and autonomous vehicles through signalized intersections," *IEEE Internet of Things Journal*, 2020.

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Dr. Michael hunter (email: michael.hunter@ce.gatech.edu), Georgia Institute of Technology for developing digital twin of the MLK Smart Corridor and guidance through filed testing.

Dr. Dalei Wu and Dr. Yu Liang (email: dalei-wu@utc.edu), UTC for developing mathematical and RL-based global optimization.

Abhilasha Saroj (email: sarojaj@ornl.gov), ORNL for working on HIL and CAVE Lab.

II.1.6 Energy Optimization of Light and Heavy-Duty Vehicle Cohorts of Mixed Connectivity, Automation and Propulsion System Capabilities via Meshed V2V-V2I and Expanded Data Sharing (Michigan Technological University)

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Start Date: October 1, 2020 End Date: June 30, 2023
Project Funding: $2,587,739 DOE share: $1,99,951 Non-DOE share: $587,788

Project Introduction

Vehicle connectivity and automated driving technologies individually have the potential to decrease energy consumption and/or safety on light, medium or heavy-duty vehicles to varying degrees depending on the traffic infrastructure and specific driving scenarios. Due to advances in sensing, perception and computing power, research and development emphasis in the mobility sector has shifted away from connectivity. Prior research has shown that driving automation with the absence of connectivity can in certain circumstances increase energy consumption [1]. The effectiveness of synergizing connectivity and driving automation technologies is the focus of this work, specifically applied to vehicle cohorts of mixed composition, light and heavy duty, and powertrains ranging from all electric to conventional internal combustion engine.

The project team is led by MTU with partners in AVL Mobility Technologies Inc. (AVL), Borg Warner, Traffic Technology Services Inc, ACM and Navistar International. The main thrusts for the team are to 1) develop a connected and automated vehicle model and hardware in the loop (CAViL) environment that includes a micro-traffic simulator, vehicle-powertrain models serving also as digital twins and embedded with AI and ML based optimizers for vehicle energy and maneuvering dynamics and 2) field a vehicle test fleet of mixed classification, propulsion and CAV capacity to validate energy optimal coordinated control of automated vehicle on various traffic infrastructure. The CAViL environment will first serve as a batch simulation tool to generate probably distribution functions of energy savings as a function of infrastructure and CAV cohort composition. Specific simulation scenarios will then be identified to be replicated on closed test track with the test CAV's running the CAViL real-time for optimal control to validate simulation and demonstrate energy and mobility improvements at multiple scales. For a cohort of mixed vehicles, the team will demonstrate a reduction of energy consumption of 10-50% [2], [3] at intersection, arterial roadway and limited access highway scenarios through connectivity and automation.

Objectives

The objectives of the project are summarized in Figure II.1.6.1 and are to demonstrate energy consumption reductions of ≥10% in simulation, on closed test track and real-world infrastructure for non-homogeneous vehicle cohorts of mixed composition relative to vehicle classification, propulsion system, connectivity, and driving automation level on the traffic infrastructures of single lane, signalized intersections, multi-lane arterial roadway and multi-lane, limited access highway. Overall, the objective is to realize energy consumption reductions at the vehicle cohort level on the driving ranges specified in Figure II.1.6.1 with a minimum of 10% and upwards of 50%. The broad range of energy savings will be illustrated with large simulation batches of widely varying parameters and boundary conditions while CAV testing will seek specific simulation scenarios for validation of real-time control through connectivity and automated, coordinated driving to reduce energy consumption while maintaining drive comfort and safety, real and perceived.

Infrastructure	Maneuver Description	Distance	** Energy Savings	Results Method	Number of Vehicles in Cohort
1.) Signalized Intersection	Approach	~ 0.4 km	20 to 50 %	Simulation, Closed Test Track, Public Roads	2 to 6
	Departure	~ 0.3 km	10 to 40 %	Simulation, Closed Test Track, Public Roads	2 to 6
2.) Arterial Corridor	Multi-lane, intersection corridor	up to 8 km	10 to 25 %	Simulation, Closed Test Track, Public Roads	4 to 8
	Speed changes & merging	up to 8 km	15 to 25 %	Simulation, Closed Test Track, Public Roads	2 to 4
3.) Highway Driving	Limited access highway driving	up to 16 km	10 to 15 %	Simulation, Closed Test Track	4 to 8
4.) Integrated Drive Cycle	Includes infrastructures 1 thru 3 in an amalgamated closed test track configuration	20 km	10 to 25 %	Simulation, Closed Test Track	4 to 8

** Anticipated range of energy savings, but highly dependent on infrastructure, maneuver, cohort composition and

Simulation & Test Factors
of Vehicles in Cohort
Propulsion Systems
Connectivity Penetration
Automation Penetration
of Lanes & Utilization (where appropriate)
Vehicle mass & road load attributes

Figure II.1.6.1 Project energy consumption reduction objectives summarized by traffic infrastructure, distances considered and scenario parameterization

Approach

To achieve the objectives of the project and create the CAViL environment that was critical to simulation and testing, the research team integrated several components to form a Systems of Systems (SoS) within the CAViL tool chain. The components included a configurable micro-traffic simulator with tunable intelligent driver models [4] and customizable traffic infrastructures, 11 vehicle-powertrain models, with 5 being direct digital twins of available CAV test vehicles, AI based energy optimizers for infrastructure-based cohort coordination and selfish CAV powertrain and a Design of Experiments (DoEx) configurator intended for large generating cases for large batch simulations. The center piece of the SoS and CAViL tool chain was proprietary software by AVL called Model. Connect that links all elements together and time synchronizes all data streams and allows two-way connectivity to external data sources (infrastructure) or vehicles. A custom 5G cellular based communication network was set up for the project leveraging SAE J2735 standard for data exchange to execute a C-V2X connectivity amongst vehicles, infrastructure, and the CAViL platform.

The SoS based CAViL is depicted in Figure II.1.6.2 along with the six-step process of controlling CAV test vehicles and demonstrated real-time, optimal energy via connected and coordinated automated driving of a non-homogeneous vehicle cohort. The process starts with 1) setting up a large patch simulation for a particular infrastructure, then 2) generating an energy reduction probability distribution function for a given infrastructure, then 3) translating a single, specific scenario hypothetical infrastructure or simulated real world infrastructure and translating it to closed test track, followed by 4) CAV test vehicle execution of the maneuver as unconnected and connected cohorts that then leads to 5) energy and vehicle dynamics post processing and then finally 6) scoring of the vehicle test data for perceived safety and drive comfort. Step 4 is conducted with the SoS CAViL running real-time with the test vehicles and connected infrastructure.

The research team has six CAV's available that constitute the test fleet with automated driving capability and verified connectivity to the SoS CAViL bench. The test fleet consists of one Class 8 heavy duty truck (Navistar) and five LDVs (MTU) that includes one battery electric compact car, two plug-in hybrid electric sedans, one plug-in hybrid mini-van and one mild hybrid full size truck. Each test vehicle has a reduced order digital twin within the SoS and receives real-time vehicle data while the SoS sends AI optimization output that will control and coordinate the test vehicles in a cohort to reduce/minimize energy consumption and maintain safe automated driving and comfortable dynamics. All vehicles, model or physical for the project are summarized in Figure II.1.6.3.

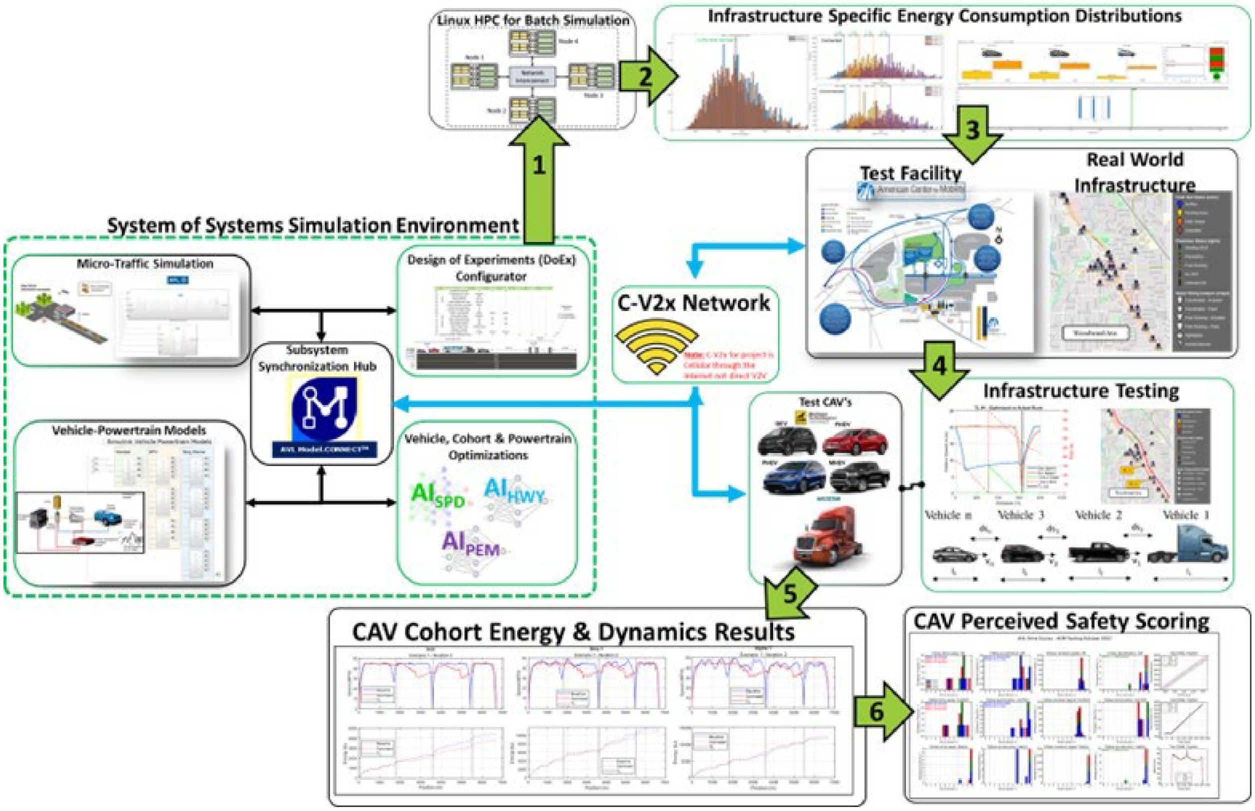


Figure II.1.6.2 Project approach for real-time cloud-based cohort CAViL for energy reduction demonstration using custom C-V2X network, AI based energy optimization and CAV test vehicles on closed test track.

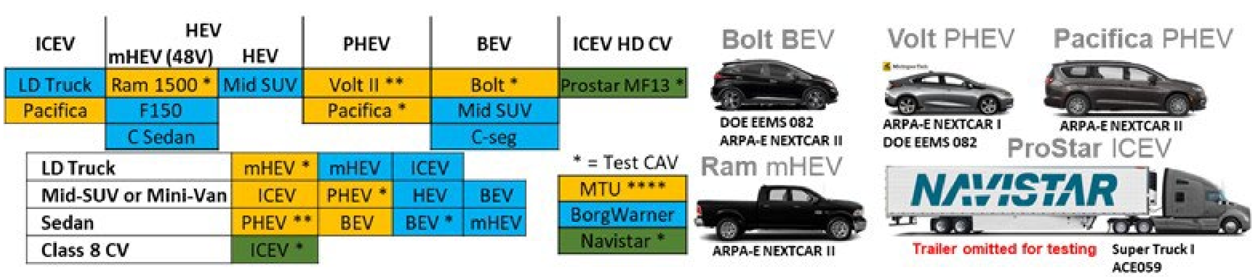


Figure II.1.6.3 Simulation and physical CAV vehicles available for modeling and test validation. All CAV test vehicles were built from prior or existing DOE/ARPA-E projects with minimal modifications/additions.

Results

During the project the research team matured the capability of the SoS based CAViL to simulate coordinated cohort vehicle control and execute vehicle tests on closed test track using AI optimization. The team's final demonstration of the project's technology development was at the end of March 2023 at ACM's track facility in Ypsilanti, Michigan. Leading up to the final demonstration, the SoS CAViL was exercised as an analysis tool to generate probability distribution functions of energy savings at a single lane, single light intersection, a multi-lane multi-light arterial roadway and a limited access highway. These simulation results were used to pull a limited number of scenarios to test at ACM and validate the simulation results and demonstrate real-time control via the SoS-based CAViL. Figure II.1.6.4 is a summary of the DoEx build out used for simulating a range of arterial roadways with various vehicle-powertrain combinations present. The column "Dec 21" was the Budget Period 1 go/no-go analysis, while the “Jan & April 23” column was a refined DoEx for the final demonstration and featured only the CAV test vehicles in the analysis. The last column, “July 23” was additional analysis targeting journal publications illustrating a wider array of vehicle-powertrains, featuring all 11 virtual models shown in Figure II.1.6.3.

ID		Parameters / Constants	Dec 21	Jan & April 23	July 23
01	Cohort	Number of Vehicles	4, 6, 8	2, 3, 4, 5 (Only test CAV's)	4, 6, 8 (all 11 CAV models allowed)
02	Cohort	Composition & Order	Random	320 Non-Repeating Permutations	Random
03	Cohort	Vehicle Spacing	20m	25m	20m
04	Cohort	Initial Velocity	=ID:16	=ID:16	=ID:16
05	Cohort	Initial Distance to Light	=ID:09	=ID:09	=ID:09
06	Cohort	Finish Line After Last Light	1000m	1000m	1000m
07	Cohort	Initial Lane Occupation	2	1	1
08	Infrastructure	Number of Traffic Lights	10	10	10
09	Infrastructure	Traffic Light Spacing	400m, 600m, 800m	400m, 600m, 800m	800m, 1600m
10	Infrastructure	Initial Light Phase	Random	Random	Random
11	Infrastructure	Green Phase Duration	30s, 45s, 60s	30s, 45s, 60s	30s, 45s, 60s
12	Infrastructure	Yellow Phase Duration	4s	4s	4s
13	Infrastructure	Red Phase Duration	30s, 45s, 60s	30s, 45s, 60s	30s, 45s, 60s
14	Infrastructure	Light Timing Type	Fixed Timing	Fixed Timing	Fixed Timing
15	Infrastructure	Number of Lanes	3	2	2
16	Infrastructure	Road Speed Limit	25mph, 35mph, 45mph	25mph, 35mph, 45mph	35mph, 45mph, 55mph
17		Random Number Generator Seed	1, 2, 3, 4, 5, 6	1, 2, 3	1, 2, 3, 4, 5, 6 repeat vehicles allowed

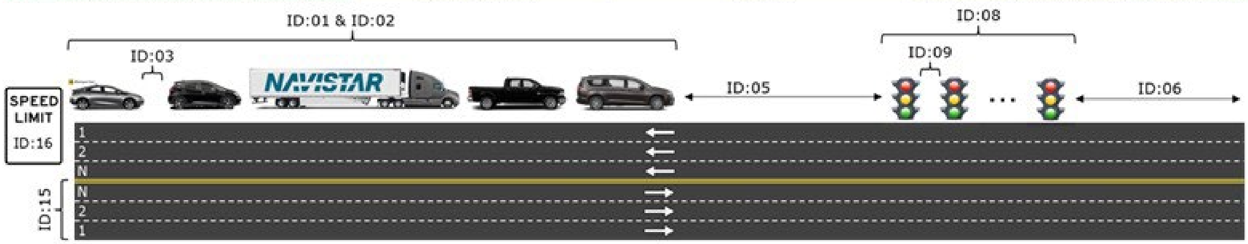


Figure II.1.6.4 Progression of arterial roadway design of experiments performed with the SoS CAViL to generate energy reduction probability distribution functions and test validation scenarios.

The DoEx results for the three infrastructures of interest as noted in Figure II.1.6.1 are contained in Figure II.1.6.5 for DoEx considering only the available CAV test vehicles as part of the simulated vehicles. The histograms represent the percent energy savings for the vehicle cohort considered comparing unconnected, typical human driver to connected and automated with optimization of energy as the main cost function. The mean energy savings for each infrastructure is provided and fit within the ranges specified in Figure II.1.6.1, satisfying the research teams analytical objectives of the project. Further data mining from these large simulations will allow for determination of the influence of vehicle position within the cohort, the degree to which powertrain electrification synergizes with the optimal cohort dynamic control and other factors, all of which will be part of future published works. The number of unconnected to connected cases is provided in Figure II.1.6.5 along with average time savings for transit for the infrastructure with intersections. For the highway infrastructure, time saved is not an outcome due to traveling at the speed limit with the optimization and energy savings solely determined by cohort reordering for the most favorable aerodynamic reduction of high energy consumers within the cohort. The mean energy savings for each CAV test vehicle across all 23,040 comparisons on highway is noted in Figure II.1.6.5.

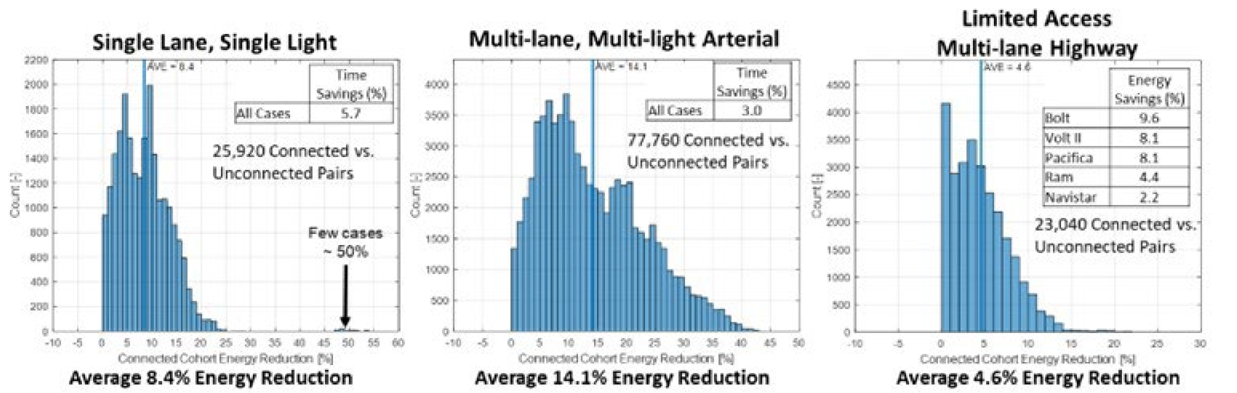


Figure II.1.6.5 Probability distribution functions by infrastructure large batch DoEx for March 2023 final project testing and demonstration.

From the probability distribution functions in Figure II.1.6.5, moderate to higher energy savings scenarios were identified and selected to recreate at ACM and overlay the modeled traffic infrastructure to demonstrate correlation of the SoS CAViL and capability to control a non-homogeneous CAV cohort in real time. A collage of images depicting the vehicle testing at ACM is provided in Figure II.1.6.6 with annotations describing the number of CAV's involved and on what type of infrastructure. In all three testing scenarios pictured in Figure II.1.6.6 the SoS CAViL was running real-time in the loop control.

Figure II.1.6.6 CAV testing collage for correlation of and demonstration of SoS CAViL for coordinated, automated cohort energy savings, March 2023, ACM closed test tracks.

Exemplary vehicle test results from testing at ACM in March of 2023 of the project's proposed coordinated CAV cohort optimal control fusing V2V and V2I through a custom 5G C-V2X network with a centralized optimization compute platform running a digital twin of the infrastructure to automated vehicle-powertrains are provided in Figure II.1.6.7, Figure II.1.6.8 and Figure II.1.6.9. In Figure II.1.6.7, results for a 5 km, multi-lane arterial scenario with 10 traffic lights (TL), 2 lanes and 35 mph speed limit are presented as traffic maze plot (left most) with unconnected vehicles in black and coordinated CAV cohort in blue. Both unconnected and connected vehicles stop at TL #2, with the AI classifier splitting the CAV cohort at TL #8. The unconnected vehicles collectively stop at five TLs while the connected CAV's stop at one TL as a cohort and half stop at a second TL. The cumulative energy difference of each vehicle traversing the infrastructure is shown in the middle plot, with individual and total energy saving percentages of the CAV's and total cohort on the far right. A 19% energy savings and 10% reduction in transit time was achieved with the test with the SoS CAViL predicting 15.8%. Although the actual test outperformed the analysis, the dynamic behavior of the test CAVs and model matched closely and that some features of the CAV's onboard energy management can't be completely replicated in the digital twin such accessory loads, special calibrations and controls dependent on battery SOC or driver power demand. Overall, the arterial roadway test demonstrations proved the sufficiency of the centralized real-time SoS CAViL approach to synergizing connectivity and drive automation through coordinated driving to reduce energy and improve transit time.

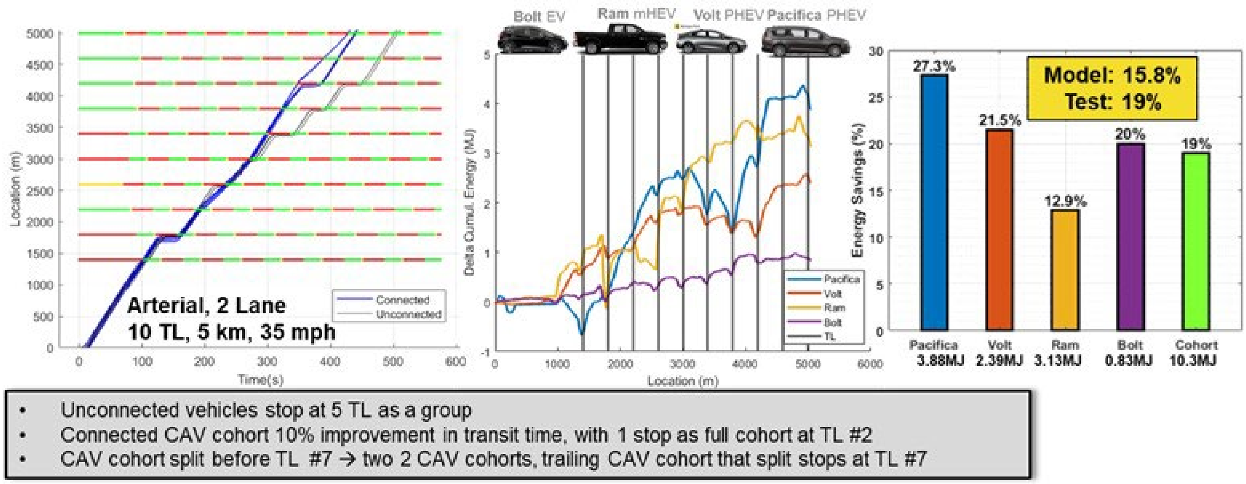


Figure II.1.6.7 Demonstration and validation test of a SoS CAViL simulation for DoEx for a two lane, 5 km arterial roadway with 10 traffic lights at 35 mph and four vehicles.

Test results for the limited access highway infrastructure are contained in Figure II.1.6.8 for a 45 mph, two-lane, 20 km distance. Unlike the arterial optimization where cohort velocity approaching and departing traffic lights as well as lane utilization and a classifier indicating cohort cohesion at edge cases of traffic light timing, the highway optimizer seeks to minimize CAV cohort total road load through aerodynamic reduction and predict least number of vehicle moves to achieve the optimal order of vehicles. No velocity profiling is suggested and the cohort travels at the speed limit of nearly the entirety of the route. The unconnected scenario has the order indicated in red—with the RAM mHEV leading followed by the Pacifica PHEV, Volt PHEV and finally the Bolt EV. The optimizer determined that the Volt PHEV should lead followed by the Bolt EV, Pacifica PHEV and the Ram mHEV trailing. The energy savings predicted by the CAViL was 6.3%, with 8.5% recorded from the CAV testing at ACM. The interesting result is that the optimization essentially places high energy efficient powertrain and/or low road load vehicles in front to provide aerodynamic reductions for trailing vehicles. As the individual CAV energy savings bar chart indicates, the high efficiency vehicles, the Bolt EV and Volt PHEV, increase energy consumption by 4.6% and 9.4%, respectively, but the four CAVs considered as a group, the total energy consumption to drive the 20 km route reduces energy consumption by 8.5%. A bit counterintuitive, but slight increases in energy consumption by high efficiency vehicles can aid in the reduction of lower efficiency (high consumption) vehicles and a net energy reduction is realized.

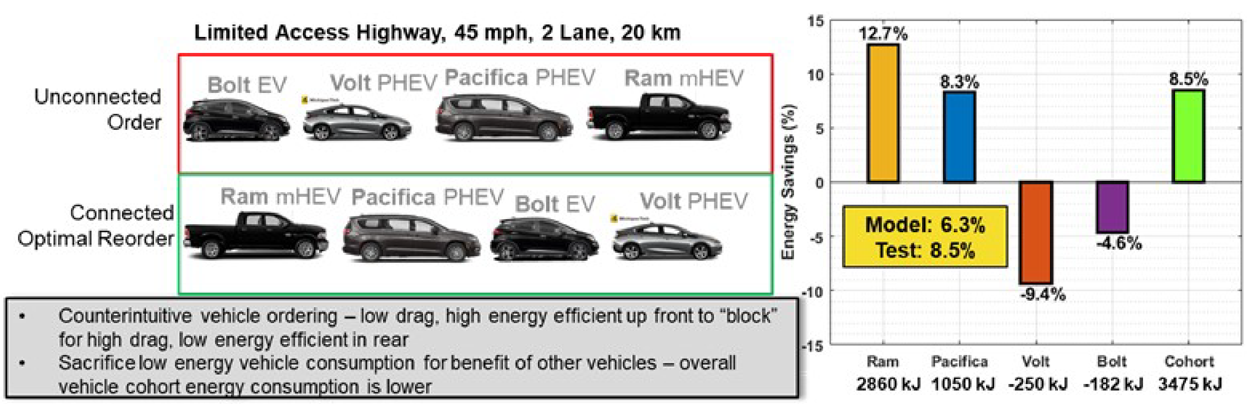
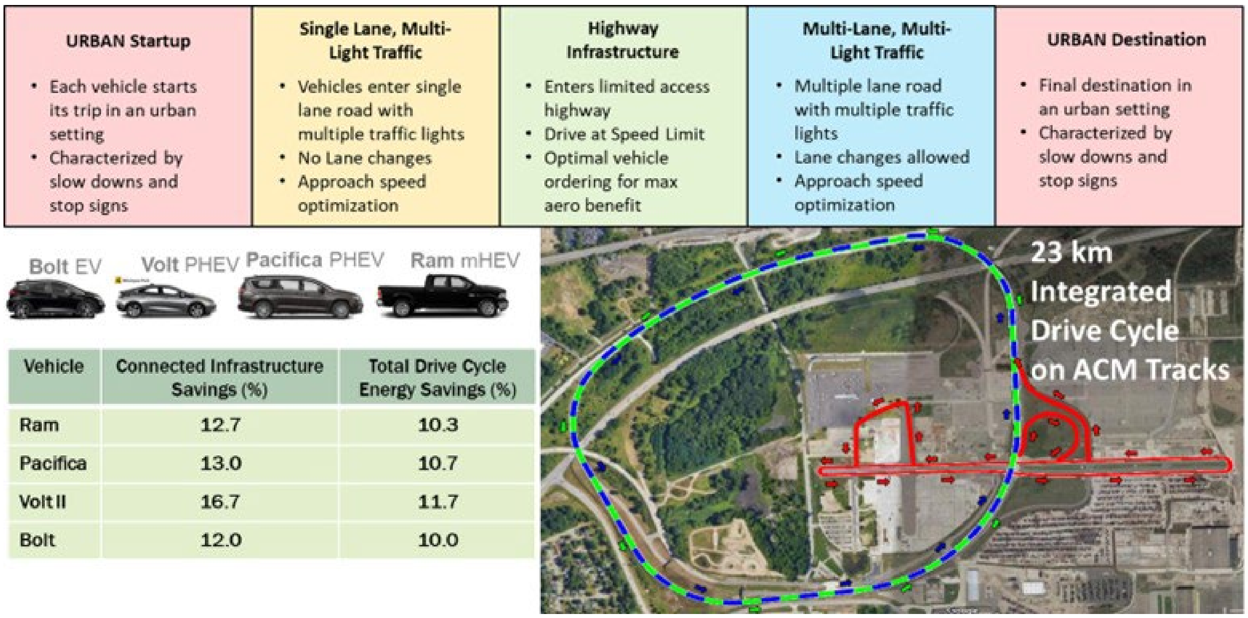


Figure II.1.6.8 Demonstration and validation test of a SoS CAViL simulation for DoEx for a two-lane, 20 km limited access highway at 45 mph and four vehicles.

An integrated drive cycle that includes urban, arterial and highway infrastructure was created and overlaid on ACM's test tracks as described and depicted in Figure II.1.6.9. Each of the light duty test CAV was then put through the route with defined speed limits for each segment and tested as unconnected with the CAViL controlling velocity via a tuned intelligent driver model [4] and as a connected CAV that merged into and out of coordinated cohort operation on certain segments of the drive cycle. The segments with connected cohort operation included the single lane, multi-light road, highway and multi-lane, multi-light arterial. Both urban sections were not performed with CAV cohort coordination. The drive cycle was approximately 23 km in length and the energy savings for each vehicle is provide in Figure II.1.6.9 for only the connected infrastructure and for the total drive cycle. All four light duty vehicles operating with connectivity and automation were able to reduce energy consumption individually between 10 and 11.7% and on average 10.6%.



Vehicle	Connected Infrastructure Savings (%)	Total Drive Cycle Energy Savings (%)
Ram	12.7	10.3
Pacifica	13.0	10.7
Volt II	16.7	11.7
Bolt	12.0	10.0

Figure II.1.6.9 Demonstration and validation test of 23 km integrated drive transposed on ACM test tracks for four LDVs

Table II.1.6.1 summarizes the results of the project in terms of simulation results and test validation performed at ACM with the CAV test vehicles. The SoS CAViL model tool chain progressively increased capability throughout the project, namely the ability to perform large batch simulations, for example performing 155,520 simulations within a week for an arterial DoEx. The model results obtained for each infrastructure meet the project objective outlined in Figure II.1.6.1 and energy reduction probability distribution functions obtained from DoEx's with varying parameters satisfied the wide range of energy reduction goals. CAV testing on closed test track of select simulation scenarios proved successful and correlated well with the selected virtual result in terms of dynamics and energy reduction.

Table II.1.6.1 Simulation and vehicle testing energy saving summary by infrastructure.

CAViL Coordinated Driving Automation Results		SoS CAViL Model				SoS CAViL Test Validation		
		Dec 21	Jan 23	April 23	July 23	Case 1	Case 2	Case 3
Single Intersection	DoEx Run Size	972	51840	51840				
	Mean Energy Savings (%)	12.0%	7.8%	8.4%		2.8%	7.6%	
Arterial	DoEx Run Size	2,916	155,520	155,520	155,520			
	Mean Energy Savings (%)	19.1%	15.8%	14.1%	17.6%	17.6%	14.7%	19.0%
Highway	DoEx Run Size	180		46,080	116,302			
	Mean Energy Savings (%)	2.3%		4.6%	6.0%	10.9%	8.5%	
Integrated Drive Cycle	Mean Energy Savings (%)					10.6%		

Conclusions

The research team successfully completed the project and satisfied the project energy reduction objectives by developing a system of system tool chain that linked vehicles, traffic infrastructure and a centralized digital twin optimization compute platform through a custom 5G communication network that produced results in both the virtual and experimental/demonstration domains. The system of system tool chain effectively became a centralized connected and automated vehicle optimizer for specific infrastructures that can run in real-time and be used in the loop to run simulations, test and validate software or test vehicle(s) hardware on track or dynamometer. The tool chain is referred to as CAViL. Neuroevolution based AI with infrastructure classifiers are the backbone of the coordinated CAV optimization method and were able to produce optimal velocity profile, lane utilization and powertrain control in the millisecond time frame. The custom C-V2X communication network using 5G cellular was able to loop communication from vehicle and infrastructure to the centralized compute platform, determine optimality from the digital twin environment, and then back to vehicles within 200 milliseconds on average. Although the team's energy reduction objectives were wide and aggressive, 10 to 50%, they depended on infrastructure, CAV cohort composition and many other factors. Leveraging the CAViL tool's ability to run large batch simulations, variation of design parameters for traffic infrastructure and vehicle composition produced energy reduction distribution functions consistent with the team's range of objectives. Closed track testing confirmed the real-time optimal control and predictive capability of the CAViL tool with results matching closely with dynamic behavior and energy savings. The research team will seek to leverage the results and seek application to additional traffic infrastructure include actuated traffic light timing and further integrate AI optimization at vehicle cohort and individual powertrain levels.

Key Publications

1. Jacquelin F., Bae, J., Chen, B., Robinette, D., Santhosh, P. et al., "Connected and Autonomous Vehicle Cohort Speed Control Optimization via Neuroevolution," IEEE Access, vol. 10, pp. 97794-97801, 2022, doi: 10.1109/ACCESS.2022.3206364.

2. Jacquelin, F., Bae, J., Chen, B., Robinette, D., Santhosh, P., Kraemer, T., Henderson, B.," Real Time Predictive and Adaptive Hybrid Powertrain Control Development via Neuroevolution," Vehicles 2022, 4, pp. 942-956. https://doi.org/10.3390/vehicles404005.

3. Jacquelin F, Bae J, Chen B, Robinette D. Neuroevolution Application to Collaborative and Heuristics-Based Connected and Autonomous Vehicle Cohort Simulation at Uncontrolled Intersection. Eng. 2023; 4(2):1320-1336. https://doi.org/10.3390/eng4020077.

4. Ma, J., Bauer, T., Ova, K., Hatcher, K. et al., "Deliver Signal Phase and Timing (SPAT) for Energy Optimization of Vehicle Cohort Via Cloud-Computing and LTE Communications," SAE Technical Paper 2023-01-0717, 2023, https://doi.org/10.4271/2023-01-0717.

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1. Liang, C.Y. and Peng, H., "Optimal adaptive cruise control with guaranteed string stability." Vehicle System Dynamics, 32, no. 4-5 (1999): 313–330.
2. Vahidi and A. Sciarretta, "Energy Saving Potentials of Connected and Automated Vehicles," Transportation Research Part C: Emerging Technologies, vol. 95, pp. 822–843, 2018.
3. F. Zhang, X., Hu, R. Langari and D., Cao, "Energy Management Strategies of Connected HEVs and PHEVs: Recent Progress and Outlook," Progress in Energy and Combustion Science vol. 73, pp. 235–256, 2019.
4. Treiber, M. and Kesting, A. Traffic Flow Dynamics: Data, Models and Simulation; Springer: Berlin, Germany, 2013.

Acknowledgements

The project PI would like to acknowledge the combined team of MTU, AVL Powertrain Engineering Inc., Borg Warner, Traffic Technology Services, ACM and Navistar for their close cooperation, resource sharing and collaborative efforts. The entire project team would also like to thank DOE for their time and commitment to the project, in particular Danielle Chou (DOT) and Daniel Nardozzi (DOE NETL).

II.1.7 Improving network-wide fuel economy and enabling traffic signal optimization using infrastructure and vehicle-based sensing and connectivity (The University of Alabama)

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Start Date: October 1, 2021 End Date: June 30, 2024
Project Funding: $2,491,009 DOE share: $1,991,319 Non-DOE share: $499,690

Project Introduction

Reduction of fuel consumption and vehicle emissions has historically been pursued by vehicle manufacturers while transportation management has been based on established traffic performance metrics. This project aims to enable improvement in network-wide fuel economy through real-time traffic signal optimization based on enhanced infrastructure- and vehicle-based sensing and connectivity capabilities. We aim to demonstrate significant reductions in network fuel consumption prior to mass adoption of connectivity technologies in vehicles but rather through infrastructure-based techniques. Optimization of connected vehicles and infrastructure operations will be aimed to minimize energy consumption, reduce emissions, and improve mobility at individual intersections, complex corridors, and the entire traffic network. We will leverage many disparate data sources to obtain current traffic states and then make changes to signal operations based on robust modeling. Signal pole mounted cameras, radars, and radio units will provide input data and edge computing hardware will implement optimization algorithms. In contrast to many traffic signal optimization approaches in literature, we will maintain strict adherence to the conventional traffic controller safety and phase transition limitations. This will allow testing of the developed methods in a real-world corridor in collaboration with local DOT officials in Spring 2024 as the project concludes. **Current results in simulation show a 14.5% reduction in system fuel consumption** relative to baseline signal control methods.

Objectives

The objective of this project is to research, develop, and validate traffic control infrastructure optimization approaches to enable a reduction in fuel consumption and emissions of ≥20% in the road network through limited real-world testing and full network simulation. To achieve the project goals, we have identified 5 major objectives that align with the primary technical challenges that must be overcome.

Objective 1: Demonstrate feasibility to acquire and synthesize data from real-world infrastructure sensors and connected vehicles into a holistic view of the current state of traffic at an intersection including trajectories of all vehicles.

Objective 2: Develop optimized operational strategies for traffic controllers based upon detailed traffic simulation models that have been calibrated with real-world traffic data.

Objective 3: Validate ability to reduce corridor fuel consumption by an average of 20% using controlled experiments at ORNL and real-world testing in in Tuscaloosa.

Objective 4: Assure operational stability through a detailed analysis of the latency, bandwidth, range, and potential interference sources of the various protocols (DSRC, C-V2X, and cellualr-vehicle-to-network) being considered for connected vehicle and infrastructure communications.

Objective 5: Develop and validate in-vehicle segment-wise trajectory optimization that can be used by connected vehicles to further improve fuel economy based on known signal timings in an upcoming corridor.

Approach

Improvement in network-wide fuel economy through real-time traffic signal optimization is being built on enhanced infrastructure- and vehicle-based sensing and connectivity capabilities. Optimization of connected vehicles and infrastructure operations is aimed to minimize energy consumption, reduce emissions, and improve mobility at individual intersections, complex corridors, and the entire traffic network. We are leveraging many disparate data sources to obtain current traffic states and then are preparing to make changes to signal operations based on robust modeling. A key feature of our approach is its potential ability to impact traffic flow at low penetration levels of connected vehicles, and the functionality will only improve with increasing levels of connectivity in the network. Combining the sensor fusion methodologies, signal optimization strategies and vehicle connectivity the project has the potential to result in an estimated system level (i.e., average across all road users) energy consumption reduction of 20%.

In the first year of the project, and after considering major anticipated events (road construction, seasonal changes, detour routes, etc.) around the Tuscaloosa region we identified the deployment corridor and have completed installation of the detection and communication hardware in collaboration with Alabama DOT and location contractors. The selected corridor consists of a three-intersection system which sees heavy truck, shopping, and residential traffic. The west most intersection at Airport Road serves significant industry located around the airport and utilizes eastbound McFarland Boulevard (US 82) to access I-20/59. The middle intersection serves a Walmart and Lowes shopping center and the east most intersection serves shopping and residential access from neighborhoods on the north side of McFarland Boulevard. Figure II.1.7.1 shows example images of the hardware deployed on a roadside signal pole as well as raw camera view and radar feeds. Figure II.1.7-2 shows overview of the full deployment corridor including satellite image overlaid with traffic simulation road network, radar units with field of view (FOV) indicated, and with inset zooms of each intersection showing location of radar units, C-V2X radio units, and 11 camera FOVs.

A comprehensive set of tools have been developed to enable this project including: micro-traffic simulation models used for development of signal control optimization strategies, vehicle models for improved fuel consumption predictions, vehicle image detection and radar return sensor fusion methods to enable real-world traffic state estimation, and finally a large set of experiments and data collection from on-board vehicle and road-side radio communications hardware. All of this data provides input into the traffic simulation models and used to develop the optimization routines with the goad to demonstrate 20% system wide fuel consumption reduction in real-world and HIL testing.

Figure II.1.7.1 (left) cameras, radars, and radio units installed on road-side signal pole shown, (middle) view from camera of incoming west-bound traffic, and (right) radar system feed and vehicle trajectory information table from one of deployment corridor intersections.

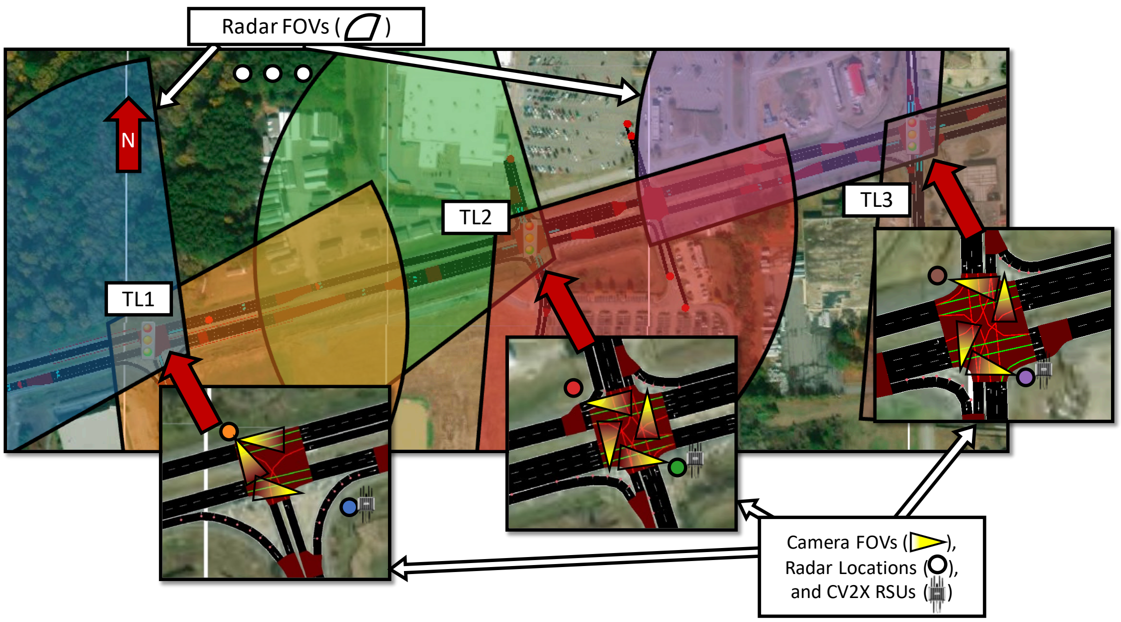

Figure II.1.7.2 Traffic simulation network of deployment corridor overlaid on aerial images with camera and radar FOVs as well as physical locations indicated, including the C-V2X RSUs.

Results

The primary results of the project in FY 2023 include continued traffic model development and calibration, sensor fusion development, signal optimization, connectivity testing and evaluation, and probe vehicle instrumentation. The following section includes subset of results including major accomplishments from start of project through the end of FY 2023:

- Sensor fusioning activities have been extended to merge trajectories of vehicles between intersections using the radar feeds resulting in up to 1.5 km long trajectories useful for calibration.
- Calibration of driver behavior is being pursued based upon radar extracted trajectories as built in car-following models do not capture real-world behavior and thus will be prone to large errors in fuel consumption estimate regardless of fidelity of the vehicle level model.

- Signal optimization efforts have shown up to 15% improvement in system wide fuel consumption relative to fixed timing control and 5% relative to actuated signal controllers.
- Additional C-V2X testing has been completed and signal controller SPaT data has been configured for transmission to connected vehicles in the network.
- Prepared HIL system for testing of vehicle level optimization augmentation based on system level signal control estimation strategies.

Sensor Fusioning: In addition to fusioning of camera/radar results at a single intersection (reported on in previous years) a methodology has been developed to merge vehicle trajectories through the entire network based on radar overlap. As shown in Figure II.1.7.2, the radar FOVs overlap provides this opportunity. The merging of trajectories within an intersection during the brief overlap is quite a bit more challenging than the merging between intersections but the workflow shown in Figure II.1.7.3 is able to successfully extract approximately 16,000 trajectories per day, (east- and west-bound) out of an average 24,000 vehicle per day total. The methodology and results are currently being prepared for publication submission.

Traffic and Vehicle Model Development: The traffic corridor under study was modeled in the SUMO software package and validated against real-world detector logs for each intersection. The logs include every detector call (from induction loops, wireless magnetic puck detectors, and radar virtual detectors as well signal status changes. These logs allowed our team to generate traffic volume and routing inputs for the simulation to capture. Figure II.1.7.2 shows the simulated corridor and previous reports have shown sample results demonstrating that results meet U.S. DOT guidelines for calibration criteria.

In last year's annual report, preliminary results were shared (and publication is expected to be available online by Summer 2024) on the importance of various driver car-following behavior model tuning parameters with average speed, acceleration, braking, following distance having the largest impact on predicted fuel consumption. Fortunately, those most important parameters can be extracted from the radar data feeds with sample results of measured and model-based distributions of driver acceleration behavior shown in Figure

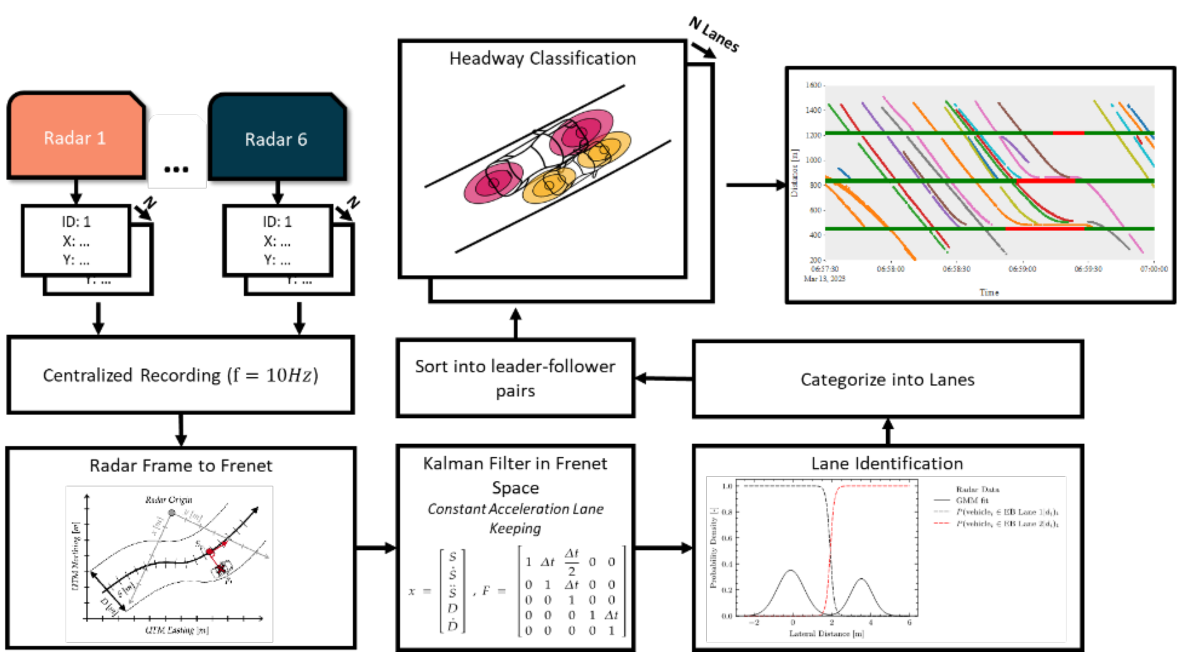

Figure II.1.7.3 Workflow of radar processing to enable extraction of complete trajectories of vehicles through the corridor. Coordinate transforms, filtering, lane identification, and identification of leader follower pairs lead to complete trajectories from which driver behavior parameters can be extracted/calibrated.

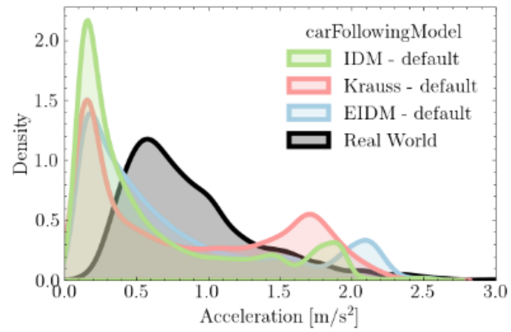

Figure II.1.7.4 Distributions of driver acceleration behavior over a four-hour window (including morning rush hour) measured by real-world roadside radar and three different car-following models with default parameters.

II.1.7.4. In all cases it is clear that the driver models do not capture the real-world behavior well for this parameter (and the same could be shown for braking, following distance, and average speed though are not shown for brevity here). While these car-following models are suitable for capturing vehicle flows they are lacking in ability to make accurate predictions of individual vehicle fuel consumption. For this reason, it is critical to calibrate and update the car-following behavior to give more accurate estimations of fuel consumption upon which the signal control optimization methods are built.

Signal Control Optimization: In evaluating the improvement of the traffic control optimization, it is critical to define a baseline upon which to compare the results. In this case, the real-world corridor has already been optimized with best practices for traffic engineering in actuated-coordinated (ACE) corridor. A more realistic baseline would be a corridor that utilizes optimized fixed-timing plans (FFC) but does include coordination and optimized timing plan. This report only includes the optimization results of the best case in which a priority metric based on vehicle speed and classification determines signal transitions. The classification includes a weighting factor for trucks over non-trucks, called Truck Speed Priority (TSP) metric cost function of the form: $VSP_i^j(t) = \alpha_i^j vs_i^j(t) + \beta_i^j wt_i^j(t) + \gamma_i^j$, which accumulates continuously for each phase (j) and each intersection (i) with optimizable weighting parameters (α, β, γ) applied to each vehicle on approach based on its speed (*vs*) and waiting time (*wt*). The relative weighting of trucks and the values of weighting parameters are optimized using genetic algorithm which runs the simulation for 4-hour period iteratively converging on optimal parameters that reduce fuel consumption. Table II.1.7.1 shows results comparing total and improvement in fuel consumption for FFC as baseline to ACE and TSP methods. indicating total fuel consumption in the 1.5km long network over a 6-hour period from 6am – 12pm (noon) capturing morning rush hour. Assuming an average 24,000 vehicles per day (see discussion above) for this corridor, the total consumption is scaled first by time and length gives results in fuel consumption per day per kilometer (L/day/km) which can be used to scale predictions to full city if desired, and then scaled by vehicle and extended to 100 km to give perspective on individual vehicle improvements (i.e., L/100 km). By implementing the state-of-the-art approaches available for traffic engineers now a 10.7% improvement in fuel consumption can be seen. **The addition of the speed and classification priority metrics results in 14.5% reduction in fuel consumption relative to baseline FFC case.**

Table II.1.7.1 Signal Optimization Results over 6 hours of simulation in 1.5 km long deployment corridor.

Signal Control Method	Fuel Consumption (L)	Fuel Consumption (L/day/km	Fuel Consumption (L/veh./100km	Improvement (%)
Fixed-time force-phase coordinated (FFC)	1682	4488	18.6	-
Actuated-cordinated NEMA eight-phase (ACE)	1495	3984	16.6	10.7%
Priority metric with tuck speed (TSP)	1433	3816	15.9	14.5%

Connectivity Hardware Testing: Previous testing has examined C-V2X and DSRC radio performance in different scenarios including dynamic tests in the deployment corridor with Cohda Wireless MK6 RSU and OBU. This real-world testing included a variety of range testing, shadowing tests with other vehicles, and more. The clearest observation to be made is that the range of the CV2X radios far exceeds the detection range

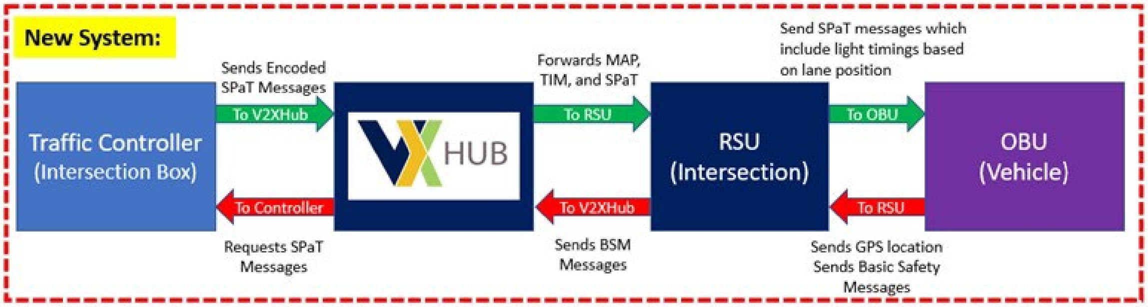

Figure II.1.7.5 Data flow illustrations between vehicle and traffic controller to share signal phasing and timing (SPaT) information and basic safety messages (BSMs).

of cameras or radars which supports the technology as a key enabler of mobility, efficiency, and safety applications in the future. Most recent progress has focused on sharing SPaT messages between traffic controller and connected vehicles and vehicle location in return. A recent development by Cohda Wireless has required substantial reworking of the teams approach as the V2XHub application is now required to be configured by the user to translate the traffic controller message format into the SPaT message the user desired. This change should enable future standardization to be easily integrated but also requires more effort for the researcher in the meantime. All pieces of the flow chart in Figure II.1.7.5 have been redeveloped and the overall system interoperability validation testing is being executed currently.

Conclusions

The project is on-track with objectives and milestones and the team is beginning preparations for real-world testing in the final phase of the project. Recent publications (see below for current journal publications, conference and papers under review are not included) have enabled confident implementation of optimization approaches and with close collaborations with state DOT officials will be key enabling factor to demonstrate real-world implementation of our methods and show reduction in system wide fuel consumption. Importantly, as is being demonstrated in this project, these approaches can be realized now while also serving as a bridge to a future connected and automated traffic fleet.

Key Publications

1. Li, Shenglin, and Hwan-Sik Yoon. 2023. “Sensor Fusion-Based Vehicle Detection and Tracking Using a Single Camera and Radar at a Traffic Intersection” *Sensors* 23, no. 10: 4888. https://doi.org/10.3390/s23104888

2. Li S, Yoon H-S. Vehicle Localization in 3D World Coordinates Using Single Camera at Traffic Intersection. Sensors. 2023; 23(7):3661. https://doi.org/10.3390/s23073661

3. Kim, Minjung, Max Schrader, Hwan-Sik Yoon, and Joshua A. Bittle. 2023. “Optimal Traffic Signal Control Using Priority Metric Based on Real-Time Measured Traffic Information” *Sustainability* 15, no. 9: 7637. https://doi.org/10.3390/su15097637

4. Schrader, M., Al Abdraboh, M., Bittle, J. (2023, July). Comparing Measured Driver Behavior Distributions to Results from Car-Following Models using SUMO and Real-World Vehicle Trajectories from Radar. SUMO User Conference 2023 (Vol. 4), Presented May 2–4, 2023 in Berlin, Germany. https://doi.org/10.52825/scp.v4i

5. Schrader, M., Wang, Q., Bittle, J. (2022, September). Extension and Validation of NEMA-Style Dual-Ring Controller in SUMO. SUMO User Conference 2022 (Vol. 3), Presented Online May 9–11, 2022. https://doi.org/10.52825/scp.v3i.115

Acknowledgements

This work also leveraged resources from The University of Alabama's Center for Advanced Vehicle Technology and the Alabama Transportation Institute.

II.1.8 Transit-Centric Smart Mobility for High-Growth Urban Activity Centers: Improving Energy Efficiency through Machine Learning (Massachusetts Institute of Technology)

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Start Date: October 1, 2020 End Date: December 31, 2023
Project Funding: $1,750,000 DOE share: $1,750,000 Non-DOE share: $0

Project Introduction

U.S. cities are developing high-growth urban activity centers that foster economic activity. But underdeveloped and ineffective transit systems fail to meet soaring mobility demands in these centers. Boston's Seaport District, for example, is emblematic of high-growth areas contributing to such inefficiencies. With large companies (e.g., General Electric) relocating their corporate headquarters to the district, employment in the district is on track to more than double from 2000 to 2035. However, public transit has not kept pace, and private shuttle buses are poorly coordinated with the broader transit system. As a result, public transit mode share is only 27% for peak period trips to the Seaport District; mode share and energy efficiency are substantially lower for the Seaport than the adjacent downtown area. While recent development in these districts have laid bare the limitations of existing transit services, there is now an unprecedented opportunity to reimagine mobility systems by better leveraging proximity to transit hubs, urban dwellers' openness to novel mobility technologies, and coordination with privately provided mobility services.

Objectives

This team proposes a transit-centric smart mobility system (TSMS) that develops operation strategies centered around public transit and coordinated with transit-aware new mobility services (e.g., private shuttles, ride-hailing, bike-sharing, etc.), to satisfy the booming mobility demands of urban activity centers and improve energy efficiency. The TSMS platform integrates operations planning, operations control, and travel demand prediction modules (Figure II.1.8.1). Specifically, the project will achieve four objectives:

1. Designing a Transit-Centric Smart Mobility System – Develop intelligent, robust, and real-time operations planning and control strategies, such as dynamic bus routing and dispatching, to serve transit and other coordinated mobility services, thus improving transit service quality, ridership, and energy efficiency.

2. Building an Integrated TSMS with Robust Deep Learning (DL), Optimization (RO), and Reinforcement Learning (RL) – Develop an integrated TSMS platform for operations planning, real-time control, and travel demand prediction by taking advantage of the increasing availability of mobility data and the state-of-the-art robust optimization, reinforcement learning, and deep learning methods.

3. Deploying Operations Control in Real-World Experiments – The team will deploy field experiments to test the proposed technologies in Boston and/or Chicago with assistance from transit agency partners.

4. Demonstrating Mobility and Energy Efficiency Impacts – The team will also demonstrate the capacity of TSMS to improve transit service quality, transit ridership, and energy efficiency, based on data from field experiments and large-scale simulations.

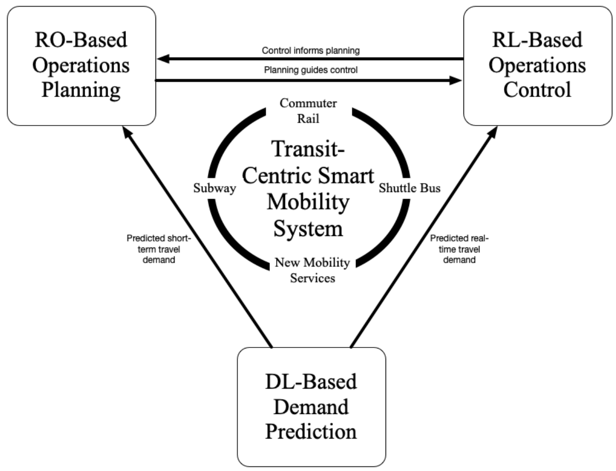

Figure II.1.8.1 Framework of TSMS

Approach

The project proposes a TSMS that can generate intelligent and robust operating plans and real-time controls to improve transit service quality, transit ridership, and energy efficiency. The approaches include four parts: 1) multi-source inputs that integrate socio-economic information, real-time transit data, and high-dimensional images and videos, 2) technology development consisting of three technology modules for transit operations planning, real-time control and demand prediction, 3) technology implementation that combines an integrated TSMS platform and two field experiments, and 4) outputs as performance metrics from both field experiments and simulations for evaluating mobility and energy efficiency.

The TSMS platform aids transit agencies in creating short-term operating plans and real-time control strategies to be adaptive to changing demand patterns, resilient to system disruptions, and responsive to real-time traffic conditions. It consists of three modules for short-term operations planning, real-time operations control, and demand prediction based on state-of-the-art machine learning methods.

1. Travel Demand Prediction with Deep Learning (DL) – To support short-term operations planning, the demand prediction module will use deep learning algorithms to predict short-term travel demand, particularly the unavoidable demand variability arising from batch arrivals of passengers transferring from commuter rail trains and airline flights.

2. Short-Term Operations Planning with Robust Optimization (RO) – This module focuses on adapting the characteristics of the transit services, such as bus routing and scheduling, to accommodate evolving passenger demand and conditions.

3. Real-Time Operations Control with Reinforcement Learning (RL) – This module uses reinforcement learning to develop real-time control strategies, such as bus holding, stop skipping, and expressing, to better serve passenger demand and provide more even bus headways.

Results

In FY 2022, the MIT team focused on the first two items in the approach section: multi-source data collection and technology development of the three technology modules, DL, RO, and RL. In FY 2023, in addition to further technology development, the team focused on the third and fourth items in the approach section: technology implementation and performance evaluation.

Technology Implementation and Evaluation: The Pilot Experiment

A pilot experiment utilizing our integrated TSMS platform was conducted. The pilot aims to apply real-time control strategies, that are adaptive to predicted demand, and supply changes due to driver absenteeism, to improve reliability of bus routes. The supervisors can monitor real-time dispatching status and recommendations via a web interface developed by the team (Figure II.1.8.2 left). The supervisors then relay the dispatching instructions to the drivers (Figure II.1.8.2 right). The pilot experiment was conducted during AM and PM rush hours of October 17-21, 2022 on Route 81 in Chicago. Route 81 has high-ridership and serves multiple transfers to the rail system. The primary strategy adopted was terminal adjustments, with RL-based and rule-based recommendations used to determine the adjustment.

Run	Bus ID	Operator ID	Time Due	Scheduled Intervals (headway)	Predicted Time	Predicted Intervals (headway)
F118	8272	42298	18:04	10/10	18:16	17/0
F125	8363	9999	18:14	10/12	18:16	0/10
F119	8277	51857	18:26	12/12	18:26	10/12
F120	9999	9999	18:39	12/13	00:00	12/16
F121	8292	58790	18:52	13/13	18:55	16/10
F122	9999	9999	19:05	13/13	00:00	0/0
F126	9999	9999	19:18	13/13	00:00	0/0
F127	9999	9999	19:31	13/13	00:00	0/0
F124	9999	9999	19:44	13/13	00:00	0/0
F139	9999	9999	19:57	13/15	00:00	0/0

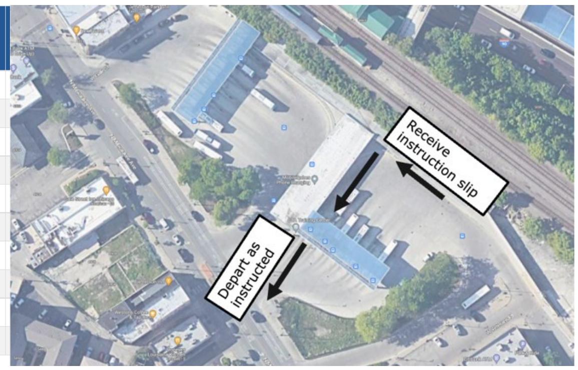

Figure II.1.8.2 Left: decision support tool interface; right: terminal workflow

The performance was diagnosed in terms of wait time (derived from headway regularity), overcrowding, and mobility energy productivity during the period of implementation and using the prior weeks as baseline. Figure II.1.8.3 left shows the performance comparison of baseline and pilot in AM rush hours according to the number of trips observed (given that the number of trips depends on the observed absenteeism). The wait time reduction observed for 14 trips was 37%, equivalent to the baseline case with two additional trips, indicating a substantial improvement brought by increased regularity. Figure II.1.8.3 right shows that 5%-20% reduction in overcrowding was achieved at each stop along the route.

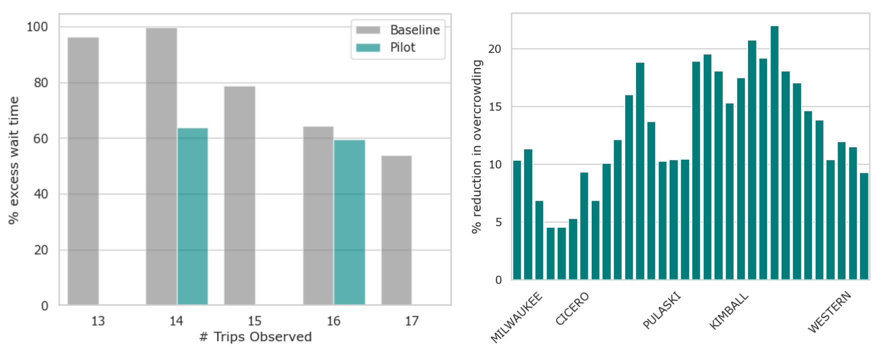

Figure II.1.8.3 Left: Wait time comparisons before and during the pilot experiment on Route 81; right: overcrowding reduction during the pilot experiment

There was an overall 6.6% MEP score improvement. Table II.1.8.1 shows the breakdown of MEP score improvement. The MEP score improved by 2.1% in the AM and 4.6% AM considering only the experienced time savings. Additionally, distance weighted energy intensity improved due to the improvement in distance-weighted occupancy, resulting in an additional 3.7% and 3.9% of MEP score improvement, leading to the overall imprveoment of 5.8% and 8.5% in the AM and PM, respectively.

Table II.1.8.1 Mobility Energy Productivity Change During the Pilot

Scenarios	AM (MEP score)	AM (MEP % Change)	PM (MEP score)	PM (MEP % Change)
Before pilot	4.33	-	4.12	-
During pilot (Time)	4.43	+2.1%	4.31	4.6%
During pilot (Time + Energy)	4.58	+5.8%	4.47	8.5%

Technology Development: Travel Demand Prediction with Deep Learning

In the demand module, the team continued to focus on uncertainty quantification of predicted demand and using multi-source inputs for demand analysis. In FY 2022, the team enhanced GNNs, which is used to predict spatiotemporal transit ridership, to incorporate data uncertainty directly into these predictions. However, our previous uncertainty quantification work lacks systematic evaluation and calibration of the quantified uncertainty, which is crucial for reliable traffic forecasting and safety-related predictions. Therefore, we developed a more refined approach—the Sparsity-aware Uncertainty Calibration (SAUC). This method is tailored for data characterized by significant sparsity and has been integrated into the latest GNN models to enhance prediction realism. Upon testing on two distinct real-world datasets, SAUC demonstrated a substantial improvement in prediction reliability, reducing errors in zero-occurrence forecasts by 20%. Figure II.1.8-4 presents the reliability diagrams comparing SAUC with benchmark models, where the diagonal lines represent perfect calibration. Figure II.1.8.4 (a) evaluates the efficacy of models in calibrating the entirety of prediction outcomes, and Figure II.1.8.4 (b) targets those possessing zero values. It is evident that both the baseline methodologies and SAUC adeptly calibrate the GNN prediction results, yet SAUC exhibits a pronounced superiority, especially in the calibration of zero values. The results demonstrate SAUC's role in bridging the uncertainty gap in predictive analytics, offering dependable guidance critical for safety-oriented decision-making processes. The work has been accepted in NeurIPS TGL Workshop.

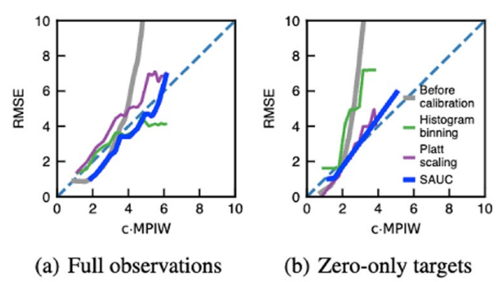

Figure II.1.8.4 Reliability diagram of different calibration methods

In addition to uncertainty quantification, we explored the use of satellite imagery and urban road networks to understand travel demand. In FY 2022, we devised a framework named "Deep Hybrid Models" (DHM) to combine unstructured image data and numeric data for travel demand analysis. Recall that the DHM embeds both unstructured data and numeric data into one latent space that is used to perform predictions. In FY22, we demonstrated higher prediction accuracy for people's mode choice prediction. This year, we explored the generative capabilities of the latent space in DHM. Image interpolation can be achieved through passing the linearly interpolated latent spaces through a decoder that is trained to reconstruct satellite imagery. Figure II.1.8.5 shows one such example. $a_1 = 0$ (S) and $a_1 = 1$ (C) representing two real images; and everything in between is interpolated imagery that does not exist in real life. Let's denote the latent spaces of (S) and (C) as z_s and z_c, and we can reconstruct (S) and (C) by passing z_s and z_c into the decoder. a_1 indicates the level of mixing, in other words, the transition from (S) to (C). For example, the image with $a_1 = 0.2$ means that the image is decoded from a latent vector formed by $(1 - 0.2)z_s + 0.2z_c$. The newly formed latent spaces not only can generate new imagery, but also possess the predictive capabilities. In other words, we could also predict the travel mode choices associated with the generated, hypothetical regions, the mode share transition is shown in the rightmost figure in Figure II.1.8.5.

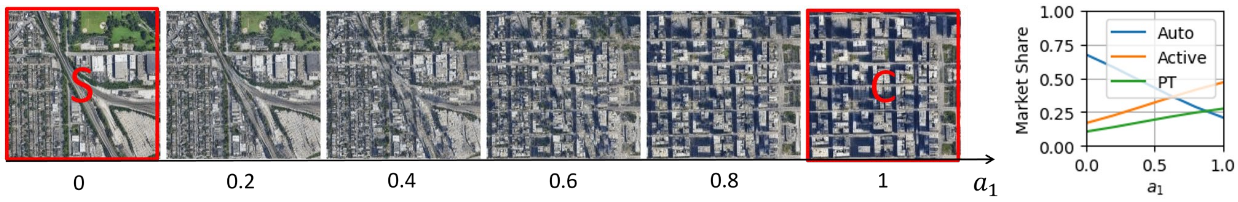

Figure II.1.8.5 Interpolated urban imagery and the predicted mode choices

DHM not only can be used on satellite imagery, but also other data sources by changing what forms the latent space. This year, we explored using urban road networks to understand travel behavior. In this research, we explored the correlations between urban road networks, socio-demographics, and travel modes. We first formed the latent space in DHM from graph embedding techniques applied to the graph formed by urban road networks, then performed logistic regression on the graph embedding readouts. Figure II.1.8.6 shows the ground truth, baseline regression and deep hybrid model results in predicting public transit mode shares. Not only does DHM outperform the baseline model's overall prediction accuracy by 20%, DHM can better capture the spatial patterns. We further explore the correlations of graph embedding values and physical road network structures and find that usually, a larger graph embedding value means a more regular and denser structure. Our observation indicate that graph-embedded road network structures are correlated with local travel mode choices and are invaluable in decrypting urban structural complexities.

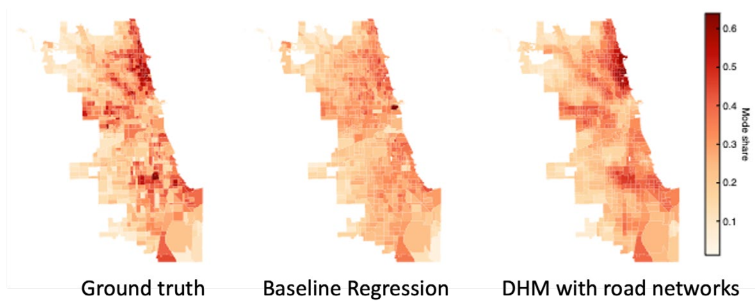

Figure II.1.8.6 Comparison of public transit mode share prediction results

Technology Development: Real-Time Operations Control with Reinforcement Learning

In preparation for the pilot field experiment, the priority of technology development of the control module was to enhance its robustness in the face of external sources of uncertainty faced during real-world deployment. To achieve these objectives the RL engine was enhanced, adopting the novel Proximal Policy Optimization method. The upgraded RL engine was trained with detailed simulations of the bus operation with uncertainty in travel times, driver compliance, and absenteeism. These properties of the operation have been overlooked by the research body and are key steps to prepare the implementation of AI-based methods in the real-world.

After the pilot field experiment, the control module was also enhanced in terms of the increased complexity in the strategies available. This was done in preparation for the full-scale field experiment, scheduled to take place in FY 2024. With the dynamic interlining strategy, a set of routes departing from the same terminal share fleet and crew to minimize overall wait time. Simulation experiments were conducted to balance performance over routes 81, 91 and 92 in Chicago which, despite having a shared terminal, show disparate performance in reliability. Figure II.1.8.7 shows the passenger wait time comparisons under different control strategies. The results indicate that when dynamic interlining was added, which involves no changes to the schedule and minimal interventions, can lead to more efficient use of resources and increase overall reliability.

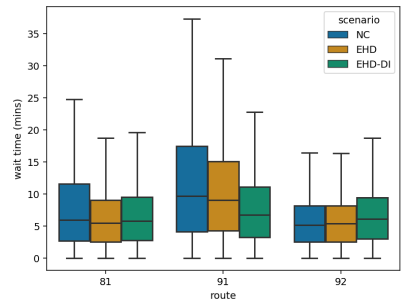

Figure II.1.8.7 Passenger wait times under different control strategies: NC – no control; EHD – even headways; EHD-DI – even headways and dynamic interlining.

Conclusions

The MIT team has made significant progress on technology implementation and evaluation in addition to development. The team has successfully implemented the pilot field experiment in Chicago. The experiment applied real-time bus control using a combination of rule-based and reinforcement learning techniques. The experiment resulted in a 37% wait time reduction, 5%-20% overcrowding reduction, and 6.6% MEP score improvement. In the demand module, the team further enhanced uncertainty quantification of spatiotemporal predictions by introducing uncertainty calibration to validate model prediction intervals, ensuring that they reflect true distributions. The team also further developed "Deep Hybrid model," which combines unstructured data (satellite imagery and road networks) with numerical data to understand travel demand. In addition to obtaining higher prediction accuracy, we explored the structure of the latent space and generation capability of this framework. In the real-time control module, the team has enhanced the robustness of the algorithms, and explored other control strategies such as dynamic interlining. Simulation has shown that dynamic interlining can further optimize resource utilization, ultimately enhancing the overall reliability of the routes.

Key Publications

1. D. Zhuang, S. Wang, H. Koutsopoulos, and J. Zhao, "Uncertainty Quantification of Sparse Travel Demand Prediction with Spatial-Temporal Graph Neural Networks", In Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (pp. 4639-4647), August 2022.

2. D. Zhuang, S. Wang, G. Wang, Y. Bu, "Uncertainty Calibration for Sparse and Discrete Spatiotemporal Forecasting", NeurIPS TGL Workshop 2023

3. Rodriguez, Joseph, et al. "Cooperative Bus Holding and Stop-Skipping: A Deep Reinforcement Learning Framework." Transportation Research Part C: Emerging Technologies, vol. 155, Oct. 2023, p. 104308, https://doi.org/10.1016/j.trc.2023.104308.

4. Q. Wang, S. Wang, D. Zhuang, H. Koutsopoulos, and J. Zhao, "Uncertainty quantification of spatiotemporal travel demand with probabilistic graph neural networks", under minor revision at IEEE Transactions on Intelligent Transportation Systems.

5. Q. Wang, S. Wang, Y. Zheng, H. Lin, X. Zhang, J. Zhao, and J. Walker, "Deep hybrid model with satellite imagery: how to combine demand modeling and computer vision for behavior analysis?", under minor revision at Transportation Research Part B: Methodological.

6. X. Guo, B. Mo, H. Koutsopoulos, S. Wang, J. Zhao, "Robust Transit frequency setting problem with demand uncertainty", 1st round of revision at IEEE Transaction on Intelligent Transportation Systems.

II.1.9 Artificial Intelligence for Optimizing Integrated Service in Mixed Fleet Transit Operations (Chattanooga Area Regional Transportation Authority)

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Start Date: October 1, 2020 End Date: June 30, 2024
Project Funding: $2,306,858 DOE share: $1,750,155 Non-DOE share: $556,703

Project Introduction

There are more than 7,000 public transit agencies in the U.S. (and many more private agencies), and together, they are responsible for serving 60 billion passenger miles each year. A well-functioning transit system fosters the growth and expansion of businesses, distributes social and economic benefits, and links the capabilities of community members, thereby enhancing what they can accomplish as a society. However, the explosion in transportation options and the complicated relationship between public and private offerings present myriad new challenges in the design and operation of these systems. There are also complex, and often competing, operational objectives that complicate the implementation of efficient services.

Chattanooga Area Regional Transportation Authority (CARTA) exemplifies the efficiency challenges that transit agencies face throughout the U.S., especially in mid-sized southern cities, where agencies have to balance the tension between improving service coverage and improving ridership. CARTA spends more than $1.1 million annually on fuel while supporting several different transportation modalities, including a fixed-route service, demand-response service (using neighborhood shuttles), and paratransit service. Through these three services, CARTA provides about 3 million passenger trips per year. The goal of the project is to integrate the operations to gain efficiency. For example, paratransit operations account for 22% of total service miles but less than 4% of passenger trips. By integrating and optimizing the operations across these three modes, we can improve system wide utilization, transit accessibility, and energy efficiency.

Objectives

Optimizing public transportation services is hard due to the size and complexity of the decision space. While it is possible to optimize these decisions separately as prior work has done, integrated optimization can lead to significantly better service. Decisions must be made facing uncertainty (e.g., future demand requests and traffic conditions). Despite these uncertainties, transit services must meet strict requirements: paratransit requests must be served within a limited time, fixed-route schedules must be closely followed, and many of these decisions must be made in real-time. Our objectives are to design automated algorithms that take into consideration the uncertainty of the system and provide a software architecture where the transit agencies can provide the services for on-demand, paratransit and fixed line by making the system more efficient.

Approach

Our approach in this project is to design decision-theoretic approaches that solve the aforementioned challenges. Combined with state of the art, sensing and big data collection and processing methods, our approach relies on deep reinforcement learning and Monte Carlo tree search-based methods. The advantage of these methods is the ability to expand the coverage of the integrated design space and find more efficient solutions than classical heuristics, which may leave vast areas of the design space unexplored, ignoring unconventional but high-quality solutions. Further, armed with the Integrated Transit and Energy Simulators we are building, the solution framework can continuously improve performance and adapt to shifting demand and traffic as more data about scenarios and energy impacts become available. Throughout the project, we leverage our prior work on machine learning models that can be used to understand and analyze the energy operations of a mixed vehicle transit fleet.

Our milestones for Phase II of the project are listed below.

1. Demonstration of the capability of the AI optimization engine to handle uncertainty in trip times, maintenance and trip roster concerns for 10% of the trips. The AI engine will be shown to operate at full trip load of the agency in the simulation.
2. Origin-destination (OD) data collection installed and operational on 50% of the fleet
3. Demonstration with simulation and comparison on the scenario with the benchmark methods. Analyses to compare energy spent per passenger per mile, passenger wait times, service coverage, and computation costs complete.
4. Report of major findings on the design of the system sent to the program manager. The AI Engine is able to schedule the two-day pilot study trips (two paratransit vehicles)

Results

The key results of our system are listed below in Table II.1.9.1.

Table II.1.9.1 Milestone Results

Milestone	Type	Description	Status
Data Collections	Technical	OD data collection installed and operation on 50% of the fleet	We have built the system to collect daily metrics from the transit vehicles (APC data), paratransit usage. There is an app that has been developed for drivers that is now available on ipad.
AI Optimization Engine	Technical	Demonstration of the capability of the AI optimization engine to handle uncertainty in trip times, maintenance and trip roster concerns for 10% of the trips. The AI engine will be shown to operate at full trip load of the agency in the simulation.	We have conducted real-experiments with CARTA for several days in April 2023, July and August 2023. Our system available at paratransit.smarttransit.ai can handle all the load and in general our system improves the scheduling efficiency by reducing VMT by > 40%
System Integration and Evaluation	Technical	Demonstration with simulation and comparison on the scenario with the benchmark methods. Analyses to compare energy spent per passenger per mile, passenger wait times, service coverage, and computation costs complete. Results and analysis sent to Project Officer.	The complete system integration and training with the CARTA operators has been done. Overall, the response to the system is very positive. We have also run the schedules with the Drivers and are now working on a final survey with the drivers that will be done. During our analysis, we saw that the shared rate went up by 30% and VMT/PMT reduced by 25%. In addition we have completed the code to perform integrated MEP analysis on the system design.

Refined Concept Testes	Go/No-Go	Report of major finding on the design of the system sent to the program manager. The AI Engine is able to schedule the two-day pilot study trips (2 paratransit vehicles). Plan for the full experiments in BP3 sent to DOE.	The design was completed early this year. It is a complete system with more than 15,000 lines of code and complex capabilities for bookings, scheduling, maintenance operations and real-time tracking. The AI Engine is able to schedule for a month.

Software Overview

The report below describes the transportation software for microtransit and paratransit operations that we created this year. The target audience is transit agencies managing these services and was initially designed for our pilot. The software includes three interfaces—an operations manager web application for dispatchers, a vehicle operator (or driver) mobile application and the user mobile application for residents to book requests. Additionally, it includes two modular optimization components—1) an offline vehicle routing problem (VRP) solver for ahead-of-time scheduling and 2) an online dynamic vehicle routing problem (DVRP) solver for same-day trip requests (based on algorithms we developed in the previous phase). The offline VRP solver is used to batch all requests ahead of time and assign vehicles to service the routes all at once. The online DVRP solver is used for same-day operations where a trip request must be assigned to a route as it arrives. The optimization components can be replaced with new solvers over time or augmented to handle various constraints specific to each transit agency by implementing programming interfaces we have designed for the offline and online tasks.

We provide an operations manager which is a web application that allows the transit agency to manage clients, take bookings, update schedules, and monitor real-time operations. Through the operations manager the agency is provided with what they need to handle both microtransit and paratransit services and is general enough to be used for any centrally managed ridepooling service. The operations manager consists of four sub-modules. There is a bookings module that allows transit agencies to take bookings over the phone or manage existing reservations booked through the user mobile application. The manifests module is for managing vehicle schedules and trip-to-vehicle assignments. Through the real-time component dispatchers can monitor and track active vehicles for more informed decision making. The real-time component is connected to the backend in a way that shows operators the real-time location of their fleet as well as the upcoming locations for each vehicle in the fleet. Lastly, the reporting module allows operators to export various components of their operations to Excel for offline or manual changes. They also have access to optimization components that can automate or recommend trip-to-vehicle assignment.

We also provide two mobile applications that can run on tablet or phone. The driver application allows vehicle operators (or drivers) to manage their routes for the day. It allows a driver to login and get their route for the day which is a schedule of users to pick-up and drop-off. The driver application interacts directly with our backend to get up-to-date routes and communicate with the dispatchers as drivers service their schedules. GPS locations are published every second to our backend so the operations managers, dispatchers and real-time algorithms have access to vehicle locations and status in real-time. Lastly, we also provide a mobile application for users to schedule trips through their smart phone. Users can also call to request trips over the phone which is then booked through the operations manager interface.

The interfaces rely on a set of APIs to manage the various automated processes and to help inform decision-making. We are running a customized Open-Source Routing Machine deployment that is augmented with historical traffic conditions. For same-day operations we rely on Mapbox for routing with real-time traffic conditions. For managing bookings, we integrated Google Maps Places Autocomplete in the text inputs related to addresses and we use a combination of Mapbox and Google Maps APIs for geo-encoding. The primary data store is MongoDB and we utilize Google Pub-Sub for pushing updates to drivers and users as well as processing real-time vehicle locations. The software is deployed on Google Cloud Platform.

Ridepolling Algorithms, Optimization and Interfaces

A key problem for transit agencies that manage ridepooling services is designing algorithms to assign requests to vehicles. In microtransit and paratransit, requests can be for some day in the future, which we refer to as ahead-of-time requests or can be for the same day. Therefore, we need two optimization components. An offline VRP solver is run ahead of time and bulk assigns trip requests to vehicle routes for the upcoming day. In this way, the offline VRP solver generates the initial vehicle schedules for the start of a day. Then when a new same-day request arrives, an online DVRP solver assigns the request to a vehicle that can accommodate the trip without violating the constraints set by the transit agency.

Trip-to-vehicle assignment is fundamentally a VRP. Most research focuses on a set of common VRP formulations that can be classified by the types of constraints applied to the system including vehicle capacities, pickups and drop-offs, and time-related restrictions (time windows). However, in real-world scenarios the constraints and objectives vary between setting (microtransit vs. paratransit) as well as between agencies. This makes it hard to use off-the-shelf algorithms from the research community. Therefore, our offline and online solvers are modular. We defined structured interfaces for both solvers so that the implementation details of the solver are decoupled from the software itself. In this way, new solvers can be added, or constraints can be adapted to fit different transit agency requirements. The solvers are made available by a REST API which means for a new solver to be incorporated the solver endpoint needs to be changed in a configuration file.

A visual representation of the real-time DVRP interface is shown in Figure II.1.9.1. The input consists of a manifest and the status for each vehicle in the fleet that is currently active. The manifest is an ordered list of locations the vehicle will visit. Each location is either a pickup or drop-off for a passenger as well as the estimated arrival time at that location. The status of the vehicle includes the current location of the vehicle, the passengers currently onboard as well as any constraints on the vehicle. Example vehicle-level constraints include the time in which the vehicle can leave the depot or must return to the depot as well as capacities for different types of passengers. The locations in the manifest correspond with existing trip requests that are currently or scheduled to be serviced. Each request has a pickup and drop-off location as well as any constraints applied to that request. Common constraints may be time windows for which the pickup or drop-off must be serviced, the number of passengers on this trip as well as types of passengers (wheelchair passengers, ambulatory passengers). The new trip request or set of new trip requests includes the same information as the existing requests but these requests are not yet assigned to any vehicle yet. The goal of the DVRP solver is to assign these new trip requests to vehicles in a way that does not violate any constraints and optimizes an objective function. Both the constraints and objective function are set by the transit agency through a SmartTransit-AI configuration file. For routing, we generate a travel time and distance matrix indexed by Node ID. A Node ID is the set of all pickup and drop-off locations for both existing and new requests as well as the depot. In this way the DVRP solver is provided with travel times and distances to be used when optimizing the manifests without having to rely on an external shortest path module. Finally, the DVRP solver must return the updated set of manifests which is processed by the SmartTransit-AI backend and pushed to the various SmartTransit-AI frontend (driver applications so that drivers have the updated routes as well as the operations manager web UI). The offline VRP interface follows a similar structure except all requests are considered new (unassigned) requests and the vehicle manifests are initially empty.

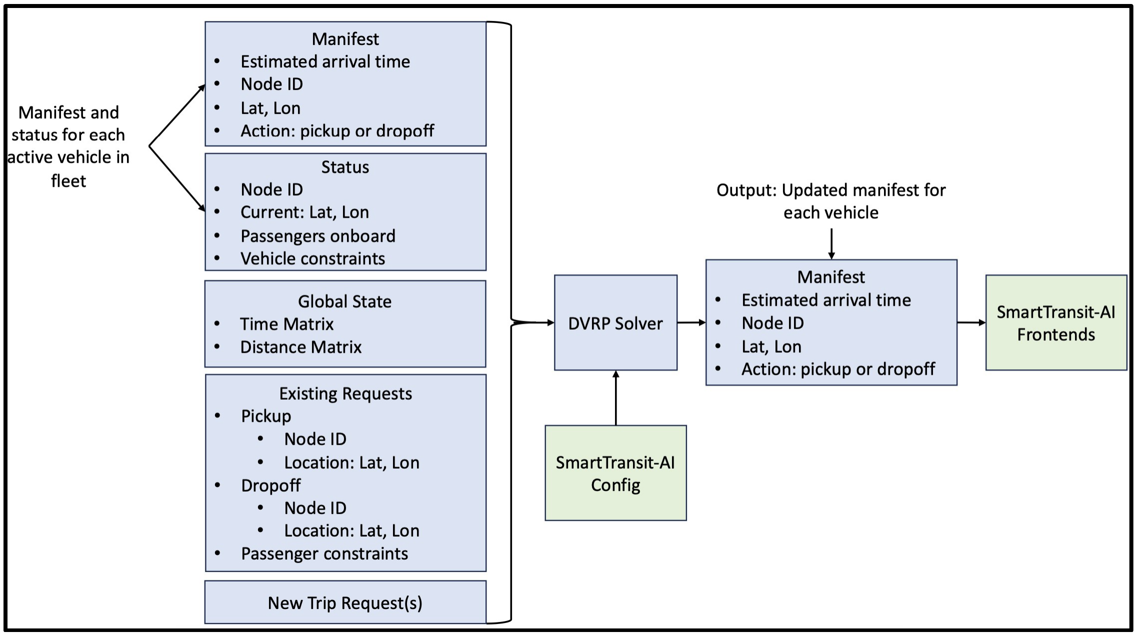

Figure II.1.9.1 DVRP interface: we defined a common interface for the input and output for incorporating real-time ride-pooling algorithms within SmartTransit-AI so that new algorithms can be quickly adapted and included within the software framework.

We provide two offline solver implementations included with the software. First is a heuristic solver implemented with Google OR-Tools that was customized to CARTA's paratransit requirements. The second solver is based on our recent work using temporal decomposition which we had to adapt for the real-world constraints of our partner agencies. Additionally, we provide a greedy online solver as well as a state-of-the-art non-myopic online solver for the paratransit setting based on recent work of ours. For the microtransit setting we are currently working on implementing a highly scalable batch solver based on shareability graphs.

Evaluation of Offline VRP Solvers

As discussed in the previous section, we implemented two offline VRP solvers within SmartTransit-AI. The first is a heuristic solver implemented with Google OR-Tools, which we refer to as the OR-Tools heuristic solver. The second is a temporal decomposition method based on our work in this space which we refer to as Rolling Horizon. Before running the pilot, we evaluated the solvers through a set of experiments outlined here. First, we evaluate the offline VRP solvers in a paratransit setting using synthetic data generated from mobility data in Chattanooga, Tennessee. Second, we evaluate the offline VRP solvers using real, historical data from microtransit services in Chattanooga (CARTA Go).

Experiment Setup

For both settings, we applied constraints based on CARTA's paratransit setting. This included the following time-window constraints: 1) if the request was appointment-based, the passenger must be dropped off by appointment and picked up no earlier than 60 minutes before the appointment, and 2) if the request was not an appointment-based request the passenger must be picked up within 15 minutes before or after the requested pickup time and then dropped off no later than 60 minutes after the requested pickup time. We also applied to vehicle capacity constraints, in line with CARTA's paratransit vehicles which had a maximum capacity of eight ambulatory passengers and two wheelchair passengers. If any of these constraints could not be met, a request could be dropped—therefore we provide a service rate metric which is the percentage of trips that could be serviced compared to all trip requests for that day.

Evaluation with Synthetic Origin-Destination Data

To evaluate our approaches, we utilized a generative demand model that generates synthetic trip requests based on movement data. Each trip is represented as an OD pair with a start and end location and the requested time of day. The generative demand model generates an OD dataset for a day and the number of trips in the dataset can be scaled up or down based on the use-case. The model can scale over 80,000 requests per day, capturing a significant percentage of trips in the region. To evaluate our offline optimization algorithms, we generated a week's worth of OD datasets each with 200 trip requests which represents CARTA's typical weekday paratransit operations.

We evaluated three offline VRP solvers on the synthetic paratransit dataset. The first solver was a heuristic solver implemented with Google OR-Tools. The objective of the Google OR-Tools heuristic solver was to minimize VMT with an additional large penalty term for dropping a trip request. We also evaluated our Rolling Horizon Solver with a penalty of 1,000 and 2,000 shown in Figure II.1.9.2. The larger penalty represented a more significant impact on dropping a trip request.

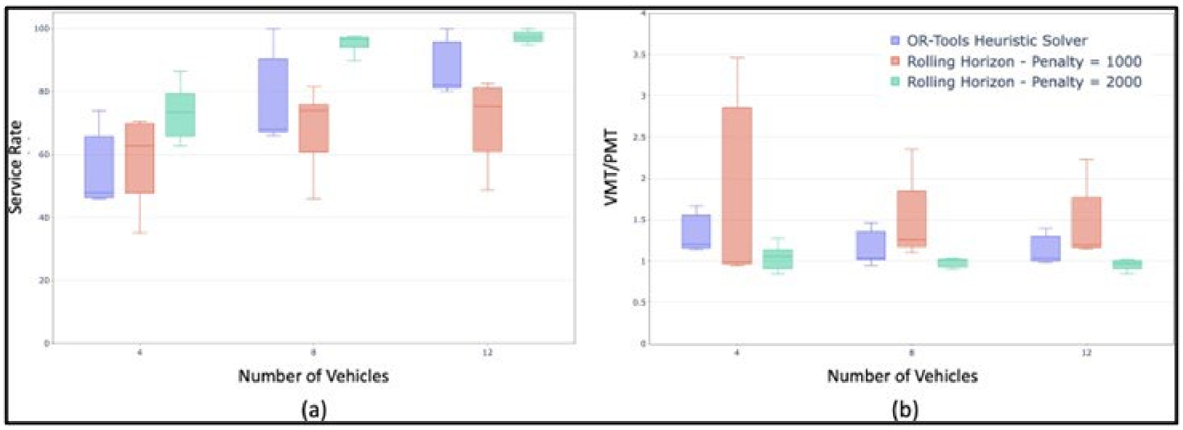

Figure II.1.9.2 (a) Service rate and (b) VMT/PMT ratio for our two offline VRP solvers – Google OR-Tools and Rolling Horizon evaluated on a synthetic dataset based on mobility patterns in Chattanooga, Tennessee. Rolling Horizon was evaluated with a penalty for dropping a booking of 1,000 and 2,000.

We assumed a vehicle capacity of 8 and applied a tight time window constraint in which requests had to be picked up within 15 minutes before or 15 minutes after the requested pickup time and the maximum detour time was 15 minutes. Any trip request that could not be serviced within these time windows was dropped. Therefore, the first metric to consider was service rate, defined as the number of trip requests serviced compared to the total number of trip requests on that day. Figure II.1.9.2(b) shows the VMT/passenger miles travelled (VMT/PMT ratio). PMT is the summation of the shortest path between origin and destination for each OD pair in the dataset for a specific day. PMT therefore represents the vehicle miles that would be required if each passenger drove directly between their corresponding origin and destination. VMT represents the total vehicle miles travelled by the vehicles over a day—including the miles a passenger or passengers were on board and when a vehicle was travelling between locations without anyone on–board. Modelling VMT/PMT in this way provides a measure of efficiency of the vehicle route plans by comparing actual miles driven compared to the miles associated with the direct shortest path of each passenger that was served. Therefore, a lower VMT/PMT ratio is more efficient and a VMT/PMT close to 1 is highly efficient and must be evaluated in the context of service rate since VMT/PMT only considers passengers served. As shown the best performing model was the Rolling Horizon with a penalty of 2000 both in the context of service rate as well as VMT/PMT—which was approximately one for 4 and 8 vehicles and less than one for 12 vehicles.

Current CARTA operations average a VMT/PMT ratio between 1.7 and 2, therefore Rolling Horizon with a penalty of 2000 has the potential to reduce VMT/PMT by 40%-50% while servicing the same number of requests with the same vehicle configurations. In this way, our methods can service the same number of requests with fewer miles travelled and thus reduces the emissions from the fleet. Alternatively, the improvement in VMT/PMT ratio indicates that we can service more requests with the same number of vehicles—assuming the new trip requests are sampled from the same distribution.

Evaluation with CARTA Go Data (Microtransit)
We also evaluated the SmartTransit-AI Google OR-Tools solver in the microtransit setting using three weekdays of real data in July 2023 from CARTA's microtransit operations (CARTA Go). The results are presented in Table II.1.9.2. The average number of Microtransit requests was 170 per day and there were four vehicles operating in the morning and four vehicles operating in the afternoon/evening. One important note is that we applied the constraints derived from the paratransit setting outlined above. However, CARTA Go did not require hard time window constraints in this respect, and therefore the column "Time Constraint Violations" refers to trips that would have violated these constraints. Conversely, this is reflected when the SmartTransit-AI routes did not service 100% of the requests since some requests could not be serviced without violating the QoS constraints. Note that all requests in the microtransit setting are non-appointment-based requests.

Table II.1.9.2 Microtransit Results Evaluation of scheduled routes for CARTA's current microtransit operations (CARTA Go) compared to routes generated by SmartTransit-AI. Results were evaluated with real microtransit trip data over three weekdays in July 2023.

Solver	VMT/PMT	Shared Rate	Service Rate	Time Constraint Violations
CARTA Go	1.51	60%	100%	31
Smart Transit AI (OR-Tools)	1.28	94%	91%	0

Real World Pilot

To test and evaluate the software in a real-world setting we ran a pilot in August 2023 with CARTA's paratransit team—CARTA Care-a-Van (CAV) in Chattanooga, TN. The goal of the pilot was to test and evaluate the software framework in a real-world paratransit setting. We chose paratransit over microtransit due to the complex system requirements with paratransit services that are often overlooked when designing general-purpose VRP solvers for mobility on demand. This includes tight time-windows associated with ADA requirements in paratransit and limited vehicles. We identified three key tasks to evaluate during the pilot. First, we aimed to evaluate the integration of our offline VRP optimizer with the CARTA CAV service. Second, we wanted to evaluate the software during real-time operations. This involved equipping drivers with the driver application on a tablet mounted in the vehicle and monitoring operations through the real-time web interface with members of the CARTA CAV operations team. Third, we wanted to gain feedback from schedulers and drivers on system usability and identify possible improvements going forward.

Pilot Design and Setup
We selected two days for the pilot—August 3, 2023, and August 10, 2023. First, for both days we exported the trip requests, driver schedules, vehicles, and scheduled manifests from CARTA's existing system. The data was imported into SmartTransit-AI. For the test dates we then generated new schedules with the Google OR-Tools offline VRP solver. On both days there were 15 vehicles available with schedules staggered between morning and afternoon shifts according to CARTA's driver and vehicle availability. There were 159 passengers total on August 3, 2023, and 129 passengers total on August 10, 2023.

CARTA CAV has strict time window constraints for two types of passenger requests. Pickup-constrained requests must be picked up within a 15-minute window before or after the requested pickup time and the passenger must be dropped off within an hour of the requested pickup time at their destination. Dropoff-constrained requests represent appointments where a passenger must be dropped off before their appointment and must be picked up no earlier than one hour before the appointment. Additionally, each vehicle had two capacity constraints—no more than 8 ambulatory passengers and two wheelchair passengers could be on a vehicle at any given time. The problem is fundamentally a resource-constrained VRP where all of the passengers known ahead-of-time must be serviced. In this way, CARTA CAV was a useful setting to test our software due to the complex set of constraints as mentioned.

For the pilot we deployed a version of the driver application to Apple TestFlight and installed the application on a set of three iPads for the CAV team. We used two iPads for testing with a series of test drives with drivers, operators and dispatchers on August 1st. After the tests we selected a route and driver for Thursday August 3rd to run with the driver application and repeated the process for August 10. The iPad was mounted in one of the standard paratransit vehicles and the driver used the application to follow his route and all updates were watched by the operations team through the web application.

Evaluation of Offline VRP Solver

The objective was to minimize VMT while servicing all trip requests. Key metrics related to performance of CARTA's original schedule compared to the schedule generated by the SmartTransit-AI offline VRP solver for both days are provided in Table II.1.9.3. As shown, the SmartTransit-AI VRP solver reduced VMT by 356 miles on August 3, 2023, and by 236 on August 10, 2023. We use VMT/PMT as the metric to represent normalized efficiency where PMT was the total shortest path distance between origin and destination for all trip requests. There was a 24% and 17% improvement in VMT/PMT over CARTA CAV's initial schedule for August 3, 2023, and August 10, 2023, respectively. The efficiency gain correlates with the finding that our implementation had a much higher Shared Rate, which is the percentage of passengers who shared their trip with at least one other passenger compared to CARTA CAV's schedule (86% compared to 61% for August 3, 84% compared to 68% for August 10).

Table II.1.9.3 Metrics Results Metrics recorded for system testing on August 3, 2023 and August 10, 2023. VMT: Vehicle Miles Travelled, VDM: Vehicle Detour Miles, VMT/PMT: Vehicle Miles Travelled to Passenger Miles Travelled, Shared Rate: percentage of trip requests that shared their trip with another passenger.

Date	Solver	VMT	VDM	VMT/PMT	Shared Rate	Passengers Served
8-3-2023	CARTA CAV	1531	601	1.14	61%	159
	SmartTransit-AI	1175	300	1.07	86%	159
8-10-2023	CARTA CAV	1269	517	1.27	68%	129
	SmartTransit-AI	1061	281	1.06	84%	129

Community Engagement

The team conducted a series of focus groups with CARTA CAV operations and driver staff beginning on February 15, 2023, which highlighted numerous issues within CARTA's operations and services. Several concerns emerged regarding GPS accuracy, with drivers experiencing discrepancies between GPS routes and actual locations, leading to delays and confusion. There were requests for more designated stops and reduced waiting times for no-show passengers. Issues with CARTA Go included distractions from sudden pickups on the screen and difficulties accessing pickup notes. CAV operations provided insights into the SmartTransit dashboard design and functional parameters.

In addition to this focus on CAV and CARTA Go demand response operations, CARTA conducted an on-board survey on CARTA Go and all fixed routes. To achieve a representative sample at the system level, every itinerary for every route was surveyed at least once. Every passenger, except children, was enlisted for participation. The sampling plan for fixed-route service and shuttle was designed for a representation at both the system-wide and route levels. A total of 1,020 surveys were collected during the period from August 8 to September 10, 2023. This data will be used to inform Phase 3 engagement and subscription plan services.

Conclusions

Enhancing public transit competitiveness is especially critical in mid-sized cities typically characterized by relatively low-density land use, widely available parking opportunities, and limited transit coverage and frequency. This project is developing operational optimization algorithms that are energy efficient and will support a more significant percentage of the population, improving their transportation choice through enhanced access to transit.

Key Publications

1. Kim, Y., D. Edirimanna, M. Wilbur, P. Pugliese, A. Laszka, A. Dubey, and S. Samaranayake. "Rolling Horizon based Temporal Decomposition for the Offline Pickup and Delivery Problem with Time Windows." In *Proceedings of the 37th AAAI Conference on Artificial Intelligence (AAAI-23)*, 2023.

2. Wilbur, M., A. Sivagnanam, A. Ayman, S. Samaranayake, A. Dubey, and A. Laszka. "Artificial Intelligence for Smart Transportation." *ArXiv*, abs/2308.07457 (2023).

3. Khaleghian, S., H. Neema, M. Sartipi, T. Tran, R. Sen, and A. Dubey. "Calibrating Real-World City Traffic Simulation Model Using Vehicle Speed Data." In *2023 IEEE International Conference on Smart Computing (SMARTCOMP)*, Nashville, TN, USA, 2023, pp. 303-308. doi: 10.1109/SMARTCOMP58114.2023.00076.

4. Wilbur, M., M. Coursey, P. Koirala, Z. Al-Quran, P. Pugliese, and A. Dubey. "Mobility-On-Demand Transportation: A System for Microtransit and Paratransit Operations." In *Proceedings of the ACM/IEEE 14th International Conference on Cyber-Physical Systems (with CPS-IoT Week 2023) (ICCPS '23)*. Association for Computing Machinery, New York, NY, USA, 2023, pp. 260–261. doi: 10.1145/3576841.3589625.

5. Sivagnanam, A. et al. "Offline Vehicle Routing Problem with Online Bookings: A Novel Problem Formulation with Applications to Paratransit." In *31st International Joint Conference on Artificial Intelligence (IJCAI)*, July 2022.

6. Sen, R., T. Tran, S. Khaleghian, M. Sartipi, H. Neema, and A. Dubey. "BTE-Sim: Fast simulation environment for public transportation." *2022 IEEE International Conference on Big Data*, 2022.

7. Sen, R., A. K. Bharati, S. Khaleghian, M. Ghosal, M. Wilbur, T. Tran, P. Pugliese, M. Sartipi, H. Neema, and A. Dubey. "E-Transit-Bench: Simulation Platform for Analyzing Electric Public Transit Bus Fleet Operations." In *Proceedings of the Thirteenth ACM International Conference on Future Energy Systems*, New York, NY, USA, 2022, pp. 532–541.

8. Wilbur, M., S. Kadir, Y. Kim, G. Pettet, A. Mukhopadhyay, P. Pugliese, S. Samaranayake, A. Laszka, and A. Dubey. "An Online Approach to Solve the Dynamic Vehicle Routing Problem with Stochastic Trip Requests for Paratransit Services." In *ACM/IEEE 13th International Conference on Cyber-Physical Systems (ICCPS)*, 2022.

9. Ayman, A., J. Martinez, P. Pugliese, A. Dubey, and A. Laszka. "Neural Architecture and Feature Search for Predicting the Ridership of Public Transportation Routes." In *8th IEEE International Conference on Smart Computing (SMARTCOMP)*, 2022.

Acknowledgements

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II.1.10 Increasing Affordability, Energy Efficiency, and Ridership of Transit Bus Systems through Large-Scale Electrification (Utah State University)

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Start Date: October 1, 2020 End Date: December 31, 2023
Project Funding: $ 2,187,500 DOE share: $ 1,750,000 Non-DOE share: $ 437,500

Project Introduction

The primary goal of this project is to promote the adoption of electric buses to improve the efficiency and effectiveness of transit bus systems. As of 2017, more than 40% of all buses in the United States were still diesel-powered, and they consumed 385.0 million gallons of diesel fuel and generated 8.6 billion pounds of carbon dioxide emissions. Diesel buses suffer from the issues of low energy efficiency, high operating costs, oil dependence, and significant tailpipe emissions. Electric buses have significant potential to reduce energy consumption and fuel costs, and they also entail lower maintenance costs than diesel buses. Moreover, battery electric buses (BEBs) generate zero tailpipe emissions and offer quiet operations and better acceleration, which can improve the quality of service and potentially increase bus ridership. To achieve the proposed goal, this project intends to help transit agencies overcome technical barriers to large-scale transit electrification by developing effective planning and operation tools and identifying strategies to improve the mobility, affordability, and energy efficiency of transit bus systems.

Objectives

This project will develop a set of innovative planning and operation models and identify improvement strategies to help transit agencies gradually and effectively deploy and operate electric buses to improve the mobility, efficiency, and affordability of transit bus systems. The objective of this project is to research, develop, apply, and validate technology and/or data solutions to reduce energy costs per mile for battery electric bus systems by at least 20% (compared to the non-optimized electrification case), lower up-front battery and charging infrastructure costs by at least 10%, and bring down bus-charging costs by at least 20%.

Approach

Electric Bus Fleet and Infrastructure Planning and Smart Operation

The research team has expanded our current model to include the bus scheduling problem and has developed a comprehensive optimization framework that addresses the combined charging infrastructure planning, vehicle scheduling, and charging management problem for BEB systems. The goal of this framework is to minimize the total cost of ownership. The team has completed numerical experiments to validate the effectiveness of the proposed model. The results demonstrate that the overall cost of ownership can be further decreased through the integration of efficient bus scheduling. Figure II.1.10.1 shows an example of the time-expanded BEB network with five BEBs and a set of timetabled service trips. Each BEB departs from the origin/source node *o* to fulfill a set of service trips and then returns to the destination/sink node.

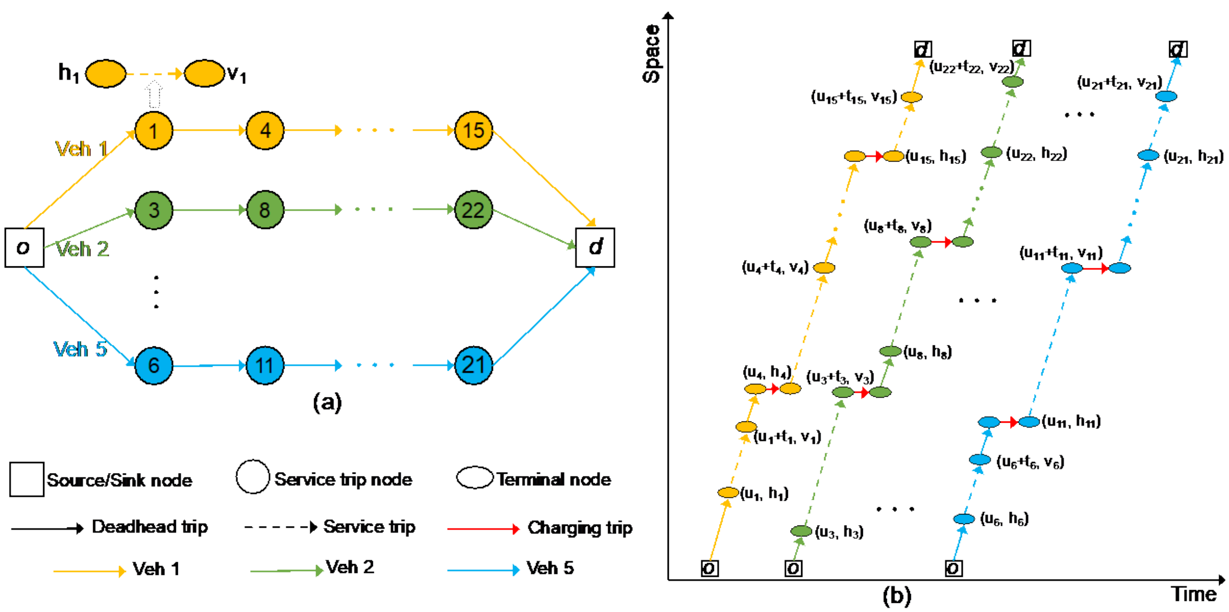

Figure II.1.10.1 An example of the time-expanded BEB network

Electric Bus Energy Estimation and Optimization

NREL has developed a transit bus-tailored RouteE for bus energy prediction, considering bus-specific features. To make RouteE-Transit more user-friendly, NREL has further developed a General Transit Feed Specification (GTFS)-based pipeline for implementing the RouteE-Transit model in the real world. Figure II.1.10.2 shows the GTFS-based framework for transit bus energy consumption estimation and service block design. For each bus service trip, its shapefile or geographic information can be obtained from GTFS data. Service trip shapefiles are matched to an underlying road network (TomTom for this project), and link attributes such as time of day, average traffic speeds, and grade are then available along the route. The energy consumption of each transit service trip is obtained by aggregating energy consumptions on road network links. With the energy consumption estimation for each service trip and timetable information from GTFS, we also simulate the operation of each service block in a transit bus system and provide system design suggestions, including battery sizing, charging station deployment, and charging scheduling.

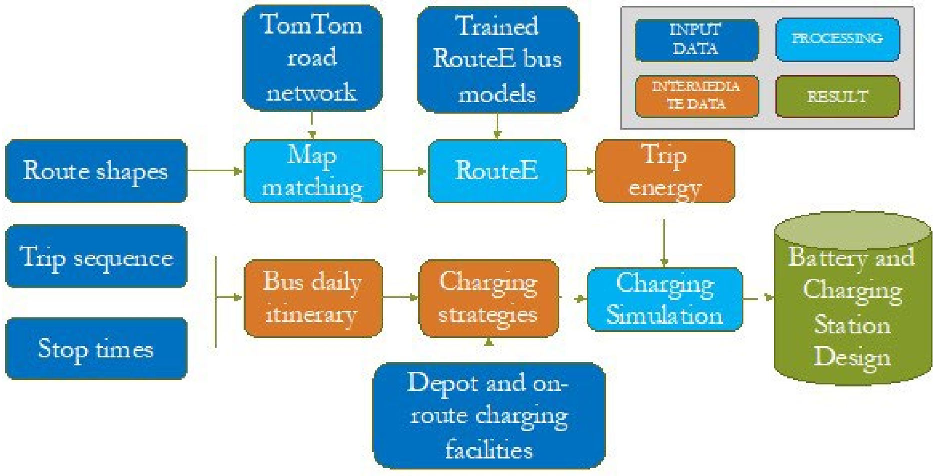

Figure II.1.10.2 GTFS-based RouteE-Transit energy consumption estimation and service block design

Grid Impact Analysis and Evaluation

To measure the effects of BEB charging on distribution networks, we have collected data from charging sessions at the Utah Transit Authority's (UTA's) Salt Lake Central station in Salt Lake City, Utah. This data was collected from the on-route bus chargers using the Open Charge Point Protocol. The Open Charge Point Protocol data include the start and end times of charging sessions and total energy used. We take this data and create a time-series power profile for the on-route chargers at the station. Additionally, we have considered how the bus charging combines with the electric light rail at the station to identify potential overlapping of peak demand or the distribution of peak demand.

A distribution network model was provided to the research team by Rocky Mountain Power, the electric utility serving the UTA's site. This model includes the electrical parameters of the power delivery equipment, such as distribution lines and transformers, and estimates of power demand for other, non-UTA loads on the network. The distribution network model varies with time by using measured load data from the utility, which is used to estimate how the loading of the network changes over time. The time-varying nature of the distribution model is crucial because it identifies times when the grid is overloaded or underutilized.

Electric Bus User Behavior Study

This task aims to explore the preferences of bus riders towards BEBs and the general public's behavioral intentions to ride public transit. In 2022, two separate surveys were designed and disseminated in Salt Lake City, Utah, to solicit riders' and the general public's typical travel behaviors and patterns, and their preferences and opinions regarding the emissions and noise performance of BEBs. The surveys also gauged participants' attitudes, social norms, and environmental awareness. Statistical analysis revealed that various factors play a role in shaping riders' perceptions regarding the electrification of transit buses. These factors include trip purpose, attitudes toward environmental concerns, and the environmental effects of BEBs, as well as non-instrumental ride factors like comfort during the journey and the social image associated with the mode of transportation. Turning to the behavioral intentions toward public transit usage, a structural equation model was estimated, which revealed the positive and direct influence of perceived behavioral control, subjective norms, and improved transit ride comfort attributes that BEBs offer. The support for transit bus electrification and green self-identity were found to indirectly influence behavioral intentions. Gaining a deeper understanding of the significance of electrification for transit riders, and also to the general public, can enable transit service providers to modify their marketing strategies, promotion strategies, and adapt their overall operations at the system level to accommodate preferences towards BEBs, and ultimately, attract more transit riders.

Results

Joint Optimization of Electric Bus Charging Infrastructure, Vehicle Scheduling, and Charging Management

We conduct numerical examples based on a real-world bus subnetwork in downtown Salt Lake City, Utah. The bus subnetwork consists of three bus routes, with a total of 70 service trips. The three routes are Route 3 (blue line), Route 6 (red line), and Route 11 (green line) in the bus system of Salt Lake City, as shown in Figure II.1.10.3. The average distances of the trips on Route 3, Route 6, and Route 11 are 7.1 miles, 15.0 miles, and 15.4 miles, while the average durations of trips on the routes is 34.8 minutes, 66.1 minutes, and 65.5 minutes, respectively. The information for each trip, including start time, end time, start terminal, end terminal, and trip length, is obtained from the UTA’s website.

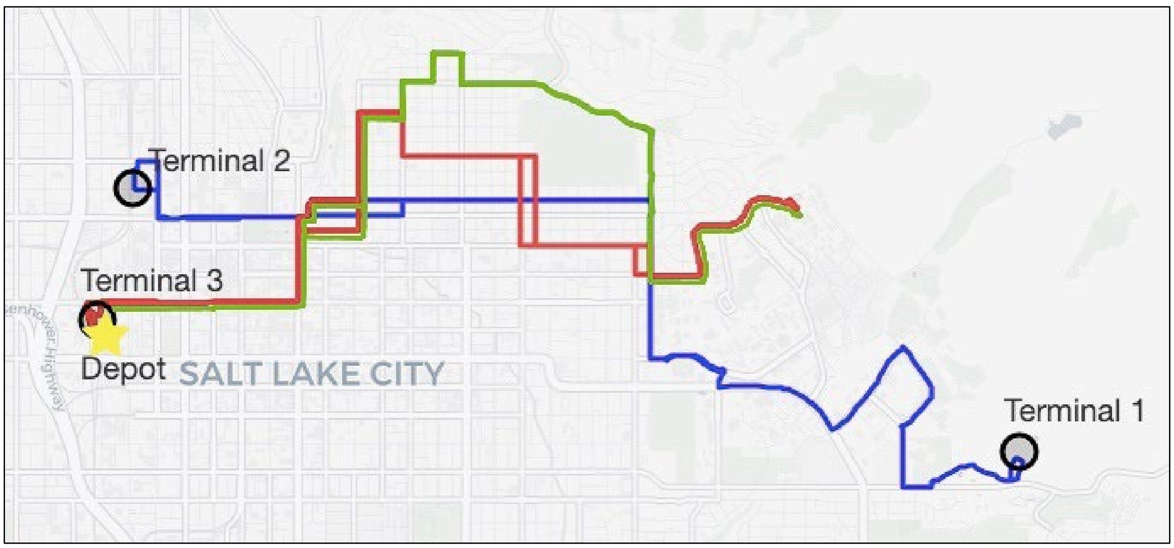

Figure II.1.10.3 A bus subnetwork in Salt Lake City, Utah

The genetic algorithm-based solution procedure is implemented using the Gurobi Optimizer in the Jupyter interface. We use the Message Passing Interface on the NREL’s HPC system, Eagle, for parallel computing. The evaluation of each chromosome is done in parallel. At each iteration, 120 processors are used to run the linear charging scheduling model for each chromosome in parallel. It took about five hours to complete the solution procedure.

The best-obtained solution is reported as follows. In total, six BEBs are needed, each carrying a 150-kWh battery. Charging stations are installed at Terminal 1 and Terminal 3, with the minimum charging power, needed being 93.3 kW and 264.3 kW, respectively; the minimum charging power needed at the depot is 46.3 kW. The amortized daily total cost of ownership is $2676.60, which consists of total vehicle costs of $666.20, charging infrastructure costs of $183.40, drivers’ salaries of $1417.40, and charging costs of $409.60 (including electricity energy costs of $234.10 and demand charges of $175.50).

Figure II.1.10-4 shows the electric bus schedule and the battery SOC profile for each BEB. In Figure II.1.10.4, the x-axis represents the time of day, while the y-axis represents the SOC of each BEB. Colored rectangles represent the trips on different routes. The pink, yellow, and purple rectangles represent the trips on Route 3, Route 6, and Route 11, respectively. We can observe that each BEB is assigned several trips from different routes. Figure II.1.10.4 also presents important information, such as each BEB's SOC being within the predefined 20%–90% range, which demonstrates that the solution for fleet size, battery size, vehicle scheduling, charging station deployment, and charging scheduling can ensure feasible operation of all service trips; in addition, most charging activities (i.e., the part where BEB SOC increases) occur during off-peak hours, effectively avoiding the high electricity rate during peak hours (i.e., 8:00 a.m. to 10:00 a.m. and 3:00 p.m. to 8:00 p.m.), thereby proving the superior performance of the charging schedules obtained from the proposed model.

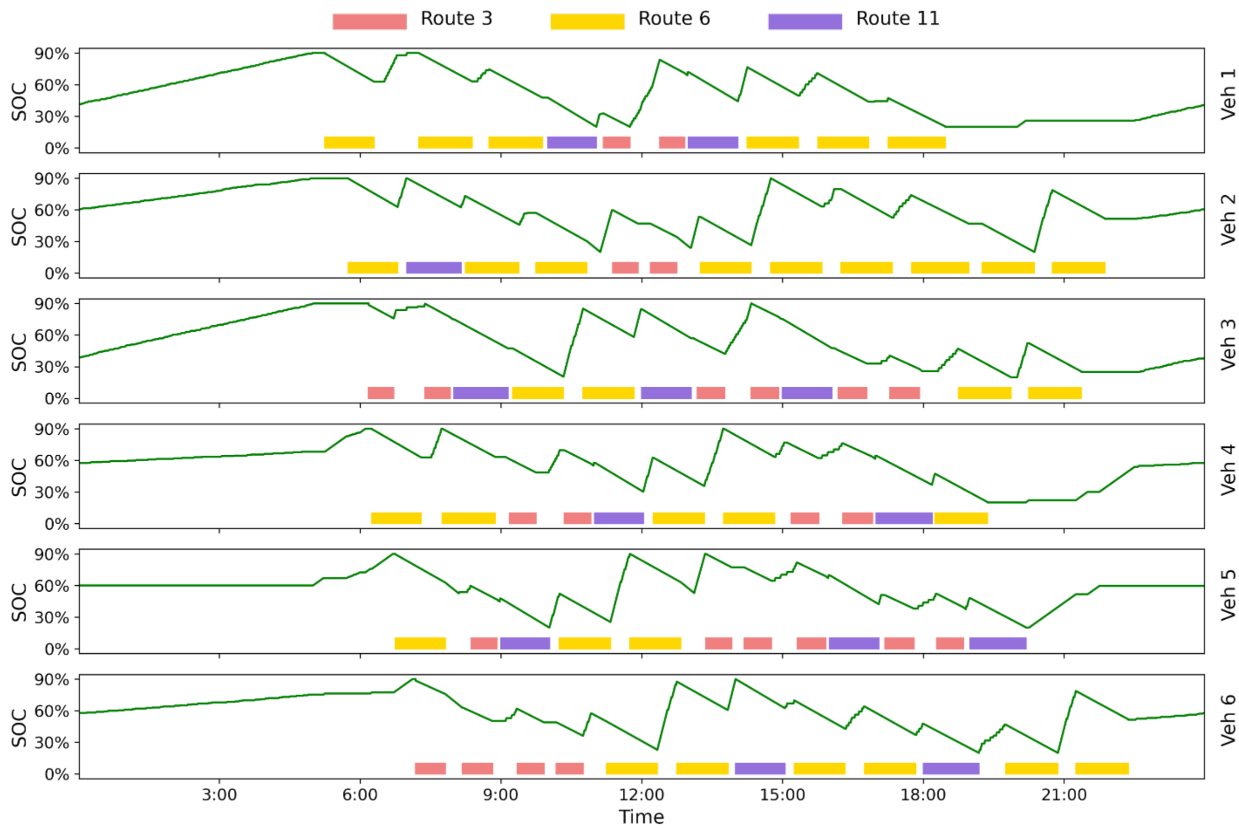

Figure II.1.10.4 Electric bus schedule and the battery SOC profile of each BEB in the optimal scenario

Electric Bus Energy Estimation and Optimization

We present the results from the GTFS-based RouteE-Transit implementation in the form of a data visualization dashboard. The dashboard prototype is developed using R-Shiny, an open-source R package for interactive web app development. The side panel menu allows the user to select from a list of available agencies and service blocks from the GTFS feed. For each service block, the dashboard displays information about the corresponding route, fuel consumption, miles driven, required battery capacity, and battery state of charge (SOC) profile. It also shows graphs comparing these key metrics against all other service blocks operated by the transit agency. Figures Figure II.1.10.5 and Figure II.1.10.6 show the dashboard prototype for service block 1153838 operated by the UTA. The state of charge graph is a straightforward analysis that uses assumptions about battery size and charge rate to estimate the SOC throughout the service block.

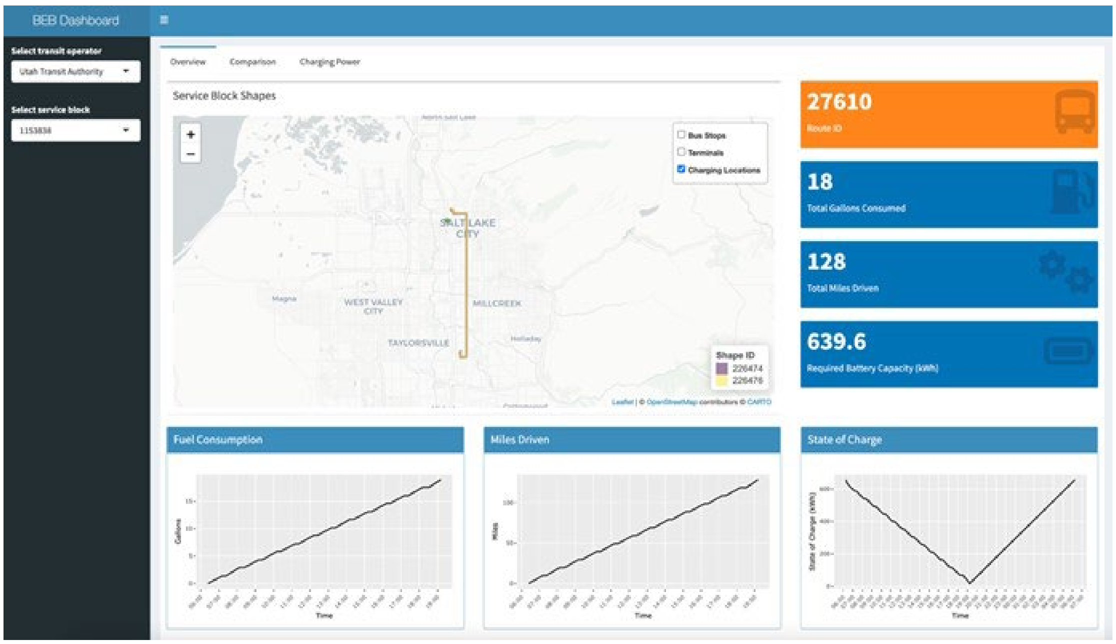

Figure II.1.10.5 RouteE-Transit dashboard prototype – main page

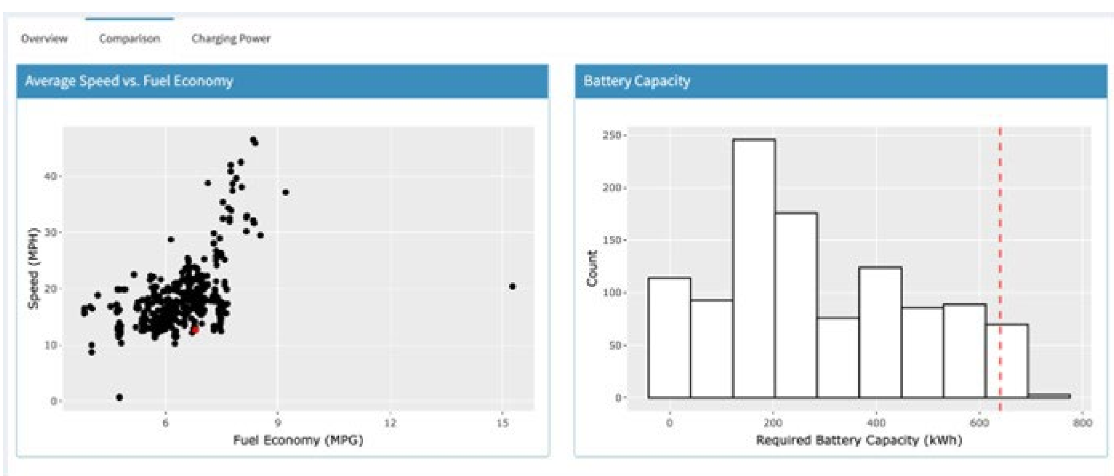

Figure II.1.10.6 RouteE-Transit dashboard prototype – agency-wide comparisons

NREL has been testing and refining the developed GTFS-based pipeline for implementing the RouteE-Transit model in the real world. NREL is also generating analysis results for a few carefully selected transit agencies/systems including the Utah Transit Authority, Williamsburg Area Transit Authority, Greater Richmond Transit Company, Hampton Roads Transit, and New Jersey Transit, which are either current or potential future partners. After finalizing the GTFS-based modeling and analysis framework, NREL will engage with the aforementioned transit agencies to solicit feedback and prioritize improvements to the RouteE-Transit dashboard and its functionality.

Grid Impact Analysis and Evaluation

The results of the grid simulation for the distribution network serving the Salt Lake Central station are shown in Figure II.1.10.7. The non-UTA loading on the network is depicted in green, with the total load displayed in blue. Due to the brief peaks caused by the UTA's loading, the fifteen-minute moving average of the total load is presented in orange. This fifteen-minute moving average is significant because the grid equipment can tolerate large, short-duration peaks, but sustained peak demand can lead to overheating of the power delivery equipment in the distribution network.

The UTA's electrified transportation load contributes 3.5% to the total energy use of the system over this time period. However, these loads account for 6.1% of the peak demand of the distribution network. This suggests that the UTA's vehicle fleet causes the grid to exhibit a higher peak demand relative to the average load on the network, thereby increasing the requirements for distribution network capacity without a proportional increase in energy consumption. This effect is also demonstrated by the use of a load factor, which is the ratio of the average load to the maximum load. For the four-day period depicted, the system has a load factor of 74.6% when the UTA loads are excluded. Including the UTA load, the load factor decreases to 73.2%, indicating less efficient utilization of the system infrastructure.

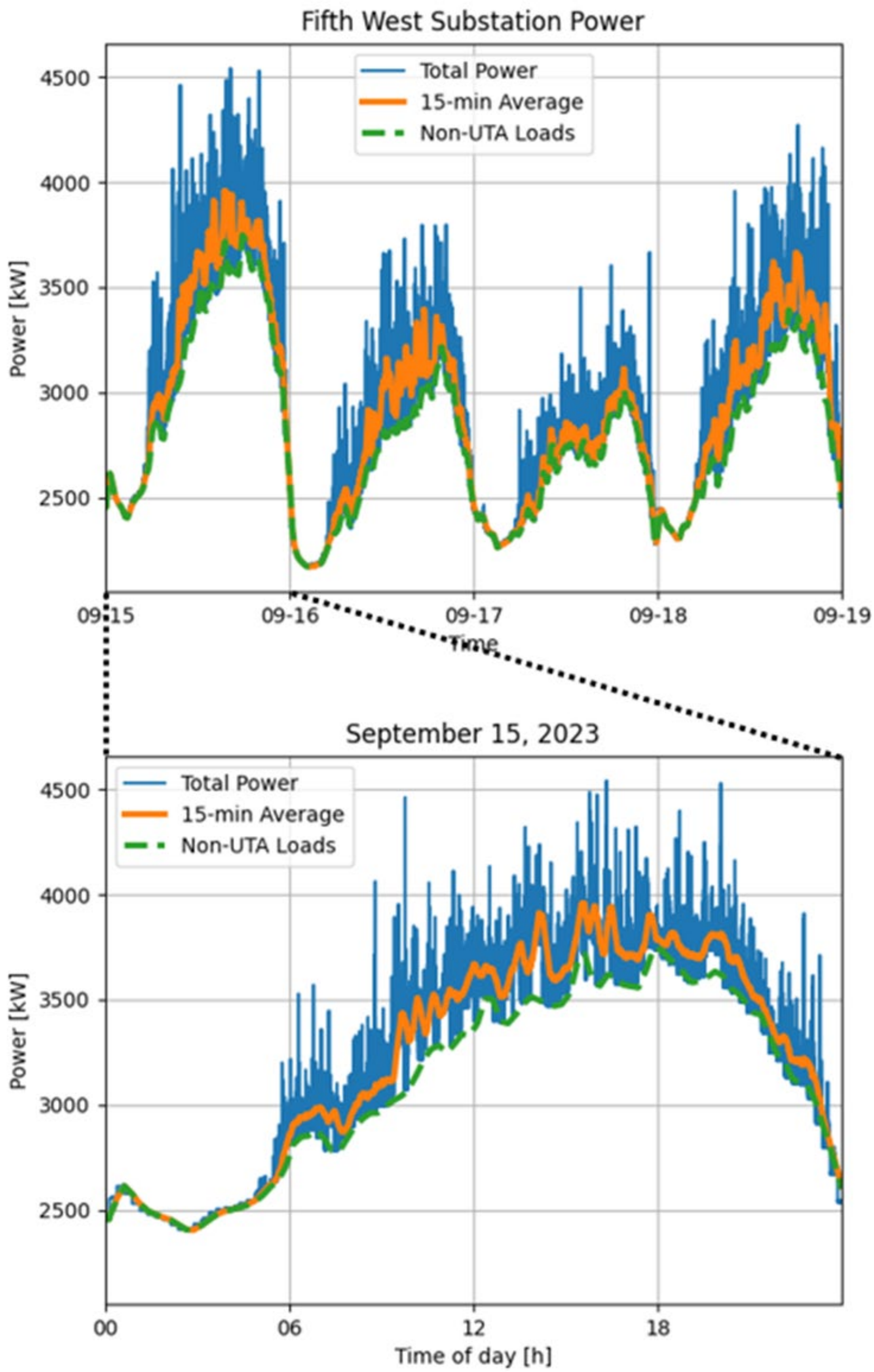

Figure II.1.10.7 Distribution network demand

Conclusions

The focus of FY 2023 was to continue the model refinement with initial implementation and validation through numerical experiments and to commence field implementation and validation. Our research has successfully expanded our model to incorporate the bus scheduling problem, leading to a more comprehensive optimization framework that synergizes charging infrastructure planning, vehicle scheduling, and charging management for BEB systems, achieving reduced total cost of ownership through enhanced bus scheduling efficiency. Complementing this, NREL has developed a specialized RouteE designed to predict bus energy needs, with plans to further refine the RouteE-Transit dashboard by seeking feedback from transit agencies. In addition, insights from 2022 surveys in Salt Lake City shed light on public and bus rider attitudes towards BEBs, with implications for environmental impact, social norms, and comfort. These findings are crucial for transit providers to tailor their strategies, potentially influencing the adoption of BEBs and the enhancement of public transit utilization.

Key Publications

1. He, Y., Liu, Z., Song, Z. (2023) Joint optimization of electric bus charging infrastructure, vehicle scheduling, and charging management. Transportation Research Part D: Transport and Environment, vol. 117, 103653.

2. Flaris, K., Gkritza, K., Singleton, P., Graul, A., Song, Z. (2023) Riders' perceptions towards transit bus electrification: Evidence from Salt Lake City, Utah. Transportation Research Part D: Transport and Environment vol. 117, 103642.

3. Paskett, A., Song, Z., Singleton, P. (2023). Barriers and Drivers to Transit Bus Electrification: The Transit Agency's Perspective. In Transportation Research Board 102nd Annual Meeting, Washington, D.C.

4. Flaris, K. (2023). Bus Riders' Perceptions Towards Electric Buses. In Transportation Research Board 102nd Annual Meeting, Washington, D.C.

5. Liu, Z., Holden, J. (2023). GTFS-data Based Electric Bus System Energy Consumption Estimation and Planning. In 2023 INFORMS Annual Meeting, Phoenix, AZ.

6. Ho, P., Liu, Z., Holden, J., Kotz, A. (2024). Data-Driven Energy Consumption Estimation for Electric Transit Buses. In Transportation Research Board 103rd Annual Meeting, Washington, D.C.

Acknowledgements

This research is supported by the Department of Energy Vehicle Technologies Office, under the EEMS Program. The authors would like to thank the UT), Tri-County Metropolitan Transportation District of Oregon, and Rocky Mountain Power for their continuous support in data sharing and field implementation.

II.1.11 Development and Validation of Infrastructure-Enabled High-Quality Perception Data to Achieve Energy Efficient Autonomous Vehicle Operation through Computation Reduction and Offloading (Western Michigan University)

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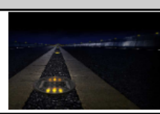
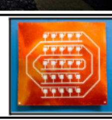
Start Date: October 1, 2021 End Date: December 31, 2024
Project Funding: $1,073,964 DOE share: $859,174 Non-DOE share: $214,790

Project Introduction

We are developing an autonomous vehicle sensing and compute load system that has a 275 W total power consumption (425 W savings from the technical baseline of 700 W). We are achieving this through elimination or reduced use of on-board sensors (replaced by infrastructure-based sensors), reduction in overall compute load needs, and computational offloading. Critical concepts for achieving the project goal include sensor development, computationally lightweight sensor fusion, and vehicle integration of our novel infrastructure-based sensor technologies. The technology developed for this project includes a suite of infrastructure-based sensors and fusion of those sensors on-board the vehicle to achieve improved autonomous vehicle energy efficiency without sacrificing safe driving performance. Our identified infrastructure technology provides the required high-quality perception data that enables energy efficient, resilient, and safe autonomous vehicle operation. Table II.1.11.1 provides a brief overview of each infrastructure-based sensor technology as well as an approximate technology readiness level (TRL) and expected energy savings. Note that the anticipated energy savings is 425W total since each anticipated sensor energy savings has overlap with other sensors.

Table II.1.11.1 The infrastructure-based sensor technology suite to be developed and integrated into an existing autonomous vehicle platform to achieve energy efficiency.

Infrastructure-Based Sensor Technology	Current	Project End	Anticipated Energy Savings	Anticipated Energy Efficiency Improvement Mechanism(s)
Chip-enabled RPM 	TRL 2	TRL 5	Up to 240W reduction	• Elimination or reduced use of on-board sensors • Reduction in overall compute load needs
Radar retroreflector 	TRL 2	TRL 5	Up to 240W reduction	
Offloading through cellular network 	TRL 3	TRL 4	Up to 185W offloaded	• Reduction in overall compute load needs
HD maps with an RTK kit  	TRL 5	TRL 6	Up to 50W reduction	• Reduction in overall compute load needs
Weather sensors  	TRL 5	TRL 6	Up to 50W reduction	• Reduction in overall compute load needs

Objectives

The overall objective of this project is to develop an autonomous vehicle sensing and compute load system that has a 275 W total power consumption (425 W savings from the technical baseline). This is accomplished by developing, utilizing, and fusing chip-enabled raised pavement markers (RPMs), radar retroreflectors, cellular network computation offloading, high-definition (HD) maps with a real-time kinematic (RTK) kit, and weather sensors. The overall outcome from this real-world demonstration is an industry adoption and government planning for CAV energy efficient infrastructure.

Objective 1 – Prototyping, Fusion, and Baseline Refinement. In this first major project objective, we are conducting proof-of-concept analysis for each of the sensors shown in Table II.1.11.1. The sensors are procured and evaluated for project efficacy. Initial data is taken and collected to ensure that the sensors can be used in the project and an initial plan for fusion of the new sensors is developed.

Objective 2 – Vehicle Integration, Fusion, and Reduced Compute Load. Chip-enabled RPM data transmissions will be obtained through a receiver connected to the vehicle's ROS architecture. Radar retroreflectors will be detected and processed using our existing Bosch radar and radar processing algorithms. Cellular network offloading will be achieved through transmission of the cloud segment to stationary computers hosted by our laboratory at Western Michigan University (WMU) and then received back at the vehicle after sensor processing. HD maps with an RTK kit will be integrated with the vehicle through upload of map data and connection to the stationary base station hosted at WMU. Mobile and stationary weather sensor data will also be transmitted to a receiver on the robotic operating system (ROS) network.

Objective 3 – On-Road Validation, Demonstrations, and Stakeholder Engagement. Routes that maximize the computation reductions will be selected and demonstrated in Kalamazoo, Michigan and Chattanooga, Tennessee. These demonstrations will be in coordination with associated stakeholders such as Michigan DOT, Tennessee DOT, Kalamazoo Area Transportation Study, Grand Valley Metropolitan Council, the city of Chattanooga, the Michigan Office of Future Mobility and Electrification, and others. Project methodology and results will be communicated with all engaged stakeholders.

Approach

Overall Technology Suite. The technology developed for this project includes a suite of infrastructure- based sensors and fusion of those sensors on-board the vehicle to achieve improved autonomous vehicle energy efficiency without sacrificing safe driving performance.

Chip-Enabled Raised Pavement Markers (CERPMs). A prototype CERPM that is capable of wireless communications to exchange information with connected and autonomous vehicles (CAVs) will be developed. The CERPM device is a novel enhancement of the traditional RPM technology that can add a variety of functional additions, including capabilities for sensing, data processing and communications to support CDA. By incorporating electronics into the RPM, many new capabilities can be realized with significant benefits for CAVs as well as for roadway monitoring. Sensing and/or transmission of road information, such as lane line locations, shoulder width, road properties, vehicle counts, average speeds, construction information, and more is possible with the proposed technology. Data processing to characterize temporal variations of the traffic state can be included.

Radar Retroreflectors. Translation of this existing radar retroreflector technology to automotive applications is conducted by evaluating the efficacy of traditional automotive detections (such as lane lines, pedestrians, cars, etc.) when using radar retroreflectors instead. If infrastructure-based radar retroreflectors are utilized correctly, it may be possible to eliminate the use of the lidar sensor, which helps our team achieve our power consumption reduction target.

Offloading through the Cellular Network. Existing products and processes from DriveU.auto's various global remote driving pilots will be used to enable robust computational offloading of any autonomous vehicle operations that are not directly connected to basic safety. The connectivity components will be able to transmit video and data on demand, with minimal set up time (<50 ms) and with minimal latency (<150 ms) to a cloud-based server that will run the relevant perception functionality.

HD Maps with an RTK Kit. HD maps provide infrastructure data such as lane line GPS coordinates, speed limits, average travel speeds, and construction information while stationary RTK kits provide 10 cm localization accuracy within a 30-mile radius. When combined, these technologies provide high-quality lane line information even during adverse weather, traffic jams, and general occlusion. This technology is in use by existing automotive and first/last mile companies but the quantification of energy savings from computation reductions has not been studied which would be a driving force for implementation.

Weather Sensors. Energy savings afforded by weather observations with respect to the CAV's onboard algorithms will be evaluated, weather conditions that maximize energy savings will be identified, and results will be communicated to stakeholders. The overall outcome is an increased awareness of the challenges and potential energy saving opportunities that occur for various weather conditions, such as heavy precipitation, reduced visibility, sun glare, and more.

Sensor Fusion. State-of-the-art approaches to infrastructure-based sensor fusion with offloading considerations currently utilize RSUs that support edge computing and two-way communication with vehicles. Our innovation is to instead optimize the energy efficiency of the vehicle itself through on-board compute load reductions. Sensor fusion remains a challenging topic in industry thus a robust and computationally lightweight demonstration would be significant. The overall impact is accelerated adoption of these infrastructure-based sensor technologies.

Results

Chip-Enabled Raised Pavement Markers (CERPMs)

A prototype of the CERPM system has been developed by a team from ORNL in collaboration with WMU. This prototype demonstrates the ability to exchange data wirelessly with the ego-vehicle. In the present state of advancement, CERPMs have the capability to transmit various data points, including GPS location, a distinct identifier, signal strength, and noise, to the receiver situated on the ego-vehicle. This transmission is facilitated by employing an energy-efficient communication protocol known as LoRa. The integration of transmission technology into the WMU Lab vehicle was accomplished by utilizing the open-source ROS. This integration was done to facilitate the subsequent evaluation and testing of the vehicles lane keeping detection system capabilities. Figure II.1.11.1 demonstrates the viability of the lane detection system within the context of autonomous vehicle systems. It effectively identifies lane lines in instances where the roads lack paint markings provided by the local DOT. The aforementioned system will utilize its inherent capability to regulate its own operations by leveraging the CERPM data. This will enable the system to effectively navigate through various routes by making use of infrastructure sensors.

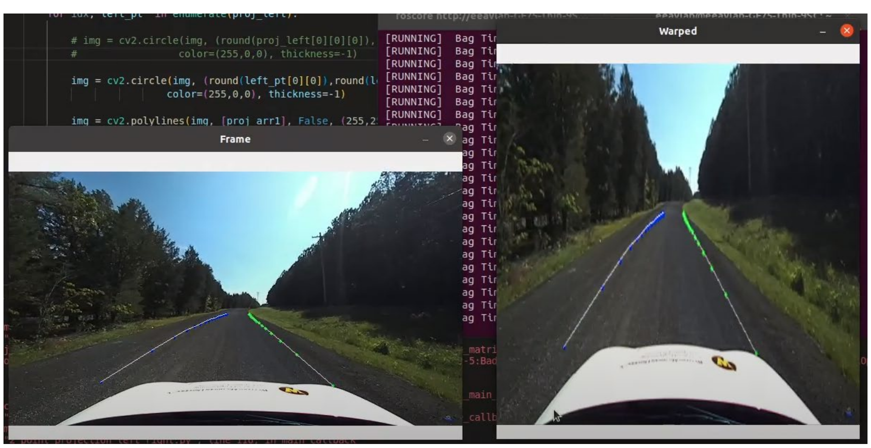
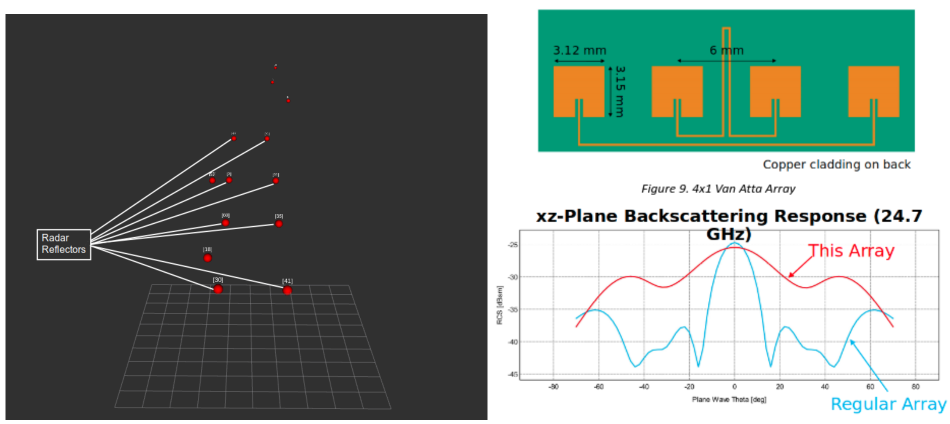


Figure II.1.11.1 ROS package integration of the CERPM system to the vehicle computing system. CERPM detections projected onto vehicle forward facing images.

Radar Retroreflectors

The radar plays a major role in object detection for driver safety since radar is able to detect objects even in adverse weather conditions. This can be used as a substitute for object detection using camera and LiDAR running YOLOv6 algorithm. Radar retroreflectors which use radar retrodirectivity to reflect incoming radar signals back in the same direction can also be used as lane-line or road markers for lane line detection. To prove this concept a set of tetrahedral radar retroreflectors were placed on the sides of the road. Figure II.1.11.2(a) (left side) shows the detections from the radar after a region of interest is defined. But these tetrahedral radar retroreflectors are about 12 x 12 inches in size making them impractical to use on actual roads. Thus, an initial design of a radar retroreflector based on the Van-Atta array as seen in Figure II.1.11.2(b) (top-right side) was designed and tested in simulation. The Van-Atta array allows for signals to be reflected back at the angle as incidence thus allowing radar signals to return back to the radar. Based on the simulation results the RCS value of the van-atta array is better than the tetrahedral array at larger incident angles. After optimizing the design for the 77 GHz automotive radar present on the test vehicle, the detection range for this van-atta design is only 7 meters. We are currently attempting to improve this range by exploring additional designs such as an active van-atta array that enhances the RCS by using a dual amplifier. Another potential design is to add additional elements to the van-atta array to increase the RCS.



(a) (b)

Figure II.1.11.2 Radar detection using the tetrahedral radar retro-reflector (a), Prototype Van atta patch antenna design retro-reflector using Feko electromagnetic simulator (b).

Offloading through the Cellular Network

The cellular network infrastructure was effectively deployed to facilitate the transmission of information from the vehicle, referred to as a streamer, to a station computer, known as a node, located in the research laboratory at WMU. The DriveU application was successfully installed on both computers, and an initial computational test was conducted to offload tasks between the node computer located in WMU's laboratory and the streamer computer situated in the vehicle. In order to validate the functionality of the system, WMU transmitted camera images to the node computer for the purpose of processing object detection algorithms employing the YOLOv7 algorithm. Figure II.1.11.3 shows the transmissioned data of the processed object detection data from the streamer to the node computer, facilitating computational offloading from the ego-vehicle.

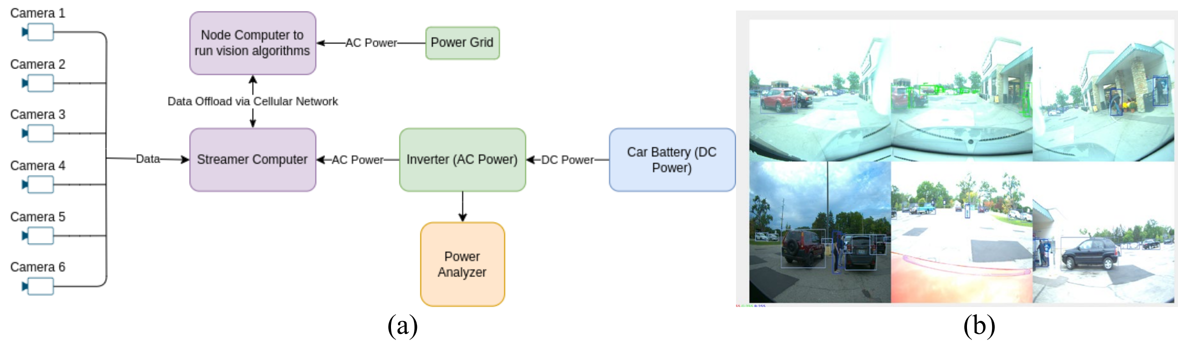


Figure II.1.11.3 Cellular offloading systems level diagram (a), six-camera image offloading through the cellular network for processing of object detection using YOLOv7 (b).

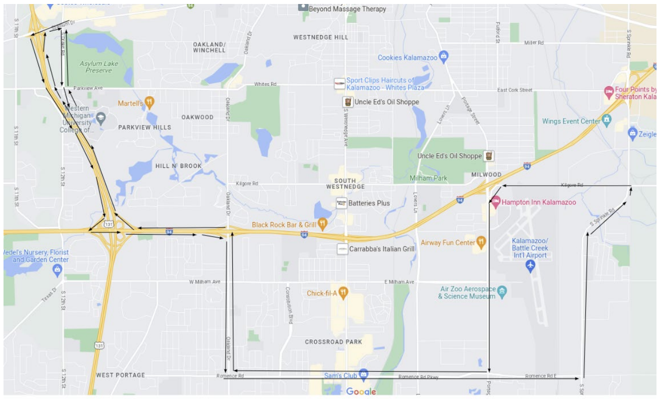
High Definition (HD) Maps with a Real-Time Kinematic (RTK) Kit

The data collection process for the HD maps involved the utilization of the Trimble Catalyst DA2 GNSS Receiver Kit in conjunction with their cloud-based service. This facilitated the acquisition of lane line data along the campus loop near WMU for the purpose of creating a high-definition map. The cartographic representation presented here was created utilizing the open source OpenStreetMap (OSM) platform. The lane line information was obtained, and subsequently, it was projected using the vehicle's on-board camera system to facilitate the visualization of the high-definition map. The vehicle demonstrates the ability to determine its precise location by utilizing the OSM HD map and RTK GNSS data. Subsequently, it accurately overlays the GNSS points onto the camera image, resulting in minimal discrepancies. The utilization of HD maps facilitates precise navigation at the level of individual lanes. This is illustrated in Figure II.1.11.4, which depicts the integration of HD maps with the vehicle's projected GPS points.

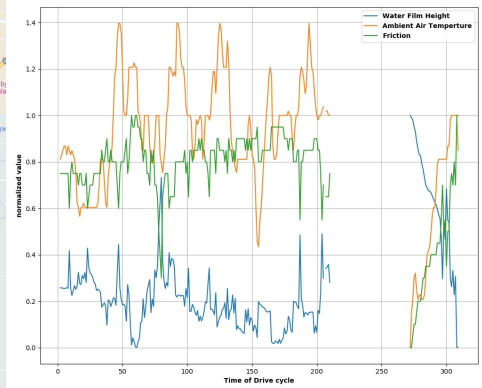
Figure II.1.11.4 projected GPS points from the HD map from a saved OSM file

Weather Sensors

We conducted a study to verify the on-vehicle weather sensor, Lufft MARWIS, using infrastructure-based weather sensor inputs from ASOS (Automated Surface Observation System) located at the Kalamazoo Battle Creek International Airport. When looking at the data compared to the ASOS information the data was correct except when the MARWIS lost power and its initial data during reboot gave incorrect values (see Figure II.1.11.5). This is a fault that has happened prior in research with DOT snowplow systems to help tracking which roads have been plowed. The viability of the on-board weather sensor may not be advantageous for an instrumented autonomous vehicle due to similar data provided by infrastructure sensors.



(a)



(b)

Figure II.1.11.5 Test route for MARWIS weather sensor verification using infrastructure sensor (ASOS) (a), MARWIS weather sensor output during test route which shows a power loss of the system(b).

Sensor Fusion

WMU and its team have evaluated the use of computationally light and heavy sensor fusion algorithms with real-world sensor data (Table II.1.11.2). For rapid prototyping and testing purposes, the team has also set up the sensor fusion pipelines in the CARLA simulator.

Table II.1.11.2 Comparison of traditional sensor fusion approach with new anticipated energy efficient sensor fusion approach: (HCL) is high compute load and (LCL) is low compute load.

	Traditional Approach	New Energy Efficient Approach
Overall conceptual sensor suite	On-vehicle: Camera, LiDAR, RADAR, GNSS, IMU, wheel odometry Off-vehicle: None	On-vehicle: RADAR, GNSS, IMU, wheel odometry Off-vehicle: CERPMs, Radar-retroreflectors, RTK corrections, HD maps
Object detection and tracking	Camera, RADAR, LiDAR: Mashed R-CNN, RANSAC, Complex-YOLO, EKF fusion	RADAR, V2X communication
Lane line perception	Camera: CNN U-Net	CERPMs (optional Radar-retroreflectors, HD maps EKF fusion)
Localization	GNSS, IMU, LiDAR, wheel odometry: LiDAR based odometry generation, Kalman Filter Fusion	GNSS with RTK, IMU, wheel odometry, HD Maps: EKF Fusion
Anticipated Compute Load	**750 W (100%)**	**275 W (40%)**

Conclusions

To date we have accomplished all Year 2 tasks associated with sensor integration to the vehicle, fusion, and compute load reduction (Objective 2). Sensor integration is complete for what is needed at this stage and preliminary compute load reduction has been observed. We are now preparing for on-road demonstrations and stakeholder engagement (Objective 3).

Key Publications

1. Sharma, Ekti, Fanas Rojas, Brown, Pesin, Wang, Huff, LaClair, Asher and Meyer. 2022. "Development and Evaluation of Chip-Enabled Raised Pavement Markers for Lane Line Detection." IEEE Sensors Conference.

Acknowledgements

We would like to acknowledge the tireless efforts of our project student leads Johan Fanas Rojas, Sachin Sharma, Nic Brown, and graduated student Nick Goberville who is now employed at Argonne National Laboratory. We would also like to acknowledge the effort of Dave Ollet from NETL in answering our questions and ensuring our success.

II.1.12 Visual-Enhanced Cooperative Traffic Operations (VECTOR) System (University of South Florida)

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Start Date: October 1, 2021 End Date: January 1, 2025
Project Funding: $4,843,654 DOE share: $3,500,000 Non-DOE share: $1,343,654

Project Introduction

Current production vehicles with CDA features (e.g., Waymo, Tesla, and other vehicles with driver-assist automation features) rely on expensive sensors, computers, and software (e.g., LiDAR, high-resolution digital cameras, GPU computers, high-definition mapping). These systems perceive limited surrounding traffic and perform redundant computations without information sharing. Further, connected and automated vehicles (CAVs) do not yet have factory-installed dedicated communication platforms for cooperative interactions with other vehicles and infrastructure [1]. To enhance energy, mobility, and safety via CDA systems, an effective communication platform needs to expand CAV's perception from the immediate neighborhood to a broader area (particularly downstream and out-of-view road conditions and traffic states) and to enable following prescriptive infrastructure guidance or seeking cooperative agreements [2].

While classic connected vehicle technologies (e.g., C-V2X and DSRC) can technically provide such a communication platform, it may take enormous infrastructure investment and an extensive period to have these connected technologies penetrate the market significantly, not to mention the uncertainties associated with recent Federal Communications Commission decisions on bandwidth allocations. Therefore, to enable CDA systems at a low cost and in a faster pace, a new low-cost and flexible communication platform based on existing infrastructure and technologies is required to quickly improve the transportation system's energy efficiency, safety and mobility. To address these limitations, this project aims to develop a Visual-Enhanced Cooperative Traffic Operations (VECTOR) system, a smart low-cost communication platform that leverages existing infrastructure and requires minimal additional hardware. Unlike traditional communication platforms, which entail high infrastructure costs and prolonged market penetration timelines, VECTOR offers a cost-effective and timely solution. Therefore, it maximizes the use of existing cameras, visual signs, and lighting devices and requires only software upgrades and minimal additional hardware.

Objectives

Overall Objectives

- Develop and validate VECTOR system for CDA in CAVs, targeting a minimum 50% cost reduction in essential CDA infrastructure compared to non-CDA solutions.
- Achieve at least a 40% cost reduction in sensing, communications, and computation compared to classic CDA technologies.
- Aim for a 40% reduction in energy consumption, an 80% reduction in non-impaired crash rates, and a 10% reduction in congestion compared to human vehicles (HVs) and non-cooperative automated vehicles.

Fiscal Year 2023 Objective

- Conduct the feasibility study of VECTOR system and test the AI sensing module (Tasks 1.1-1.3) and develop low-cost communication prototype (Tasks 1.4-1.7). Conduct the edge computing and cybersecurity work (Tasks 1.7-1.11).

Approach

The approach for this study involves the development and validation of VECTOR for efficient CDA in Tasks 1.1-1.7. These tasks are designed and tested to facilitate inter-vehicle communication by transmitting velocity data from a leading CAV to the following one. Specifically, in Budget Period 1, the whole project is divided into 4 sub-tasks: 1) Tasks 1.1-1.3 are the development of vision-based Artificial-Intelligence (AI) sensing and sensor fusion algorithms, 2) Tasks 1.4-1.6 are mainly focusing on the prototype of a low-cost communication module, 3) Tasks 1.7-1.9, focus on the development of the edge computing framework and traffic operation algorithms, and 4) Tasks 1.10-1.11, will develop a privacy-preserving algorithm and integrate it into the VECTOR system, laying the foundation for encrypted transactions with robust crypto keys. This summarizes the diverse advancements made in vehicle communication, algorithms, and hardware. The specific tasks are summarized in Figure II.1.12.1.

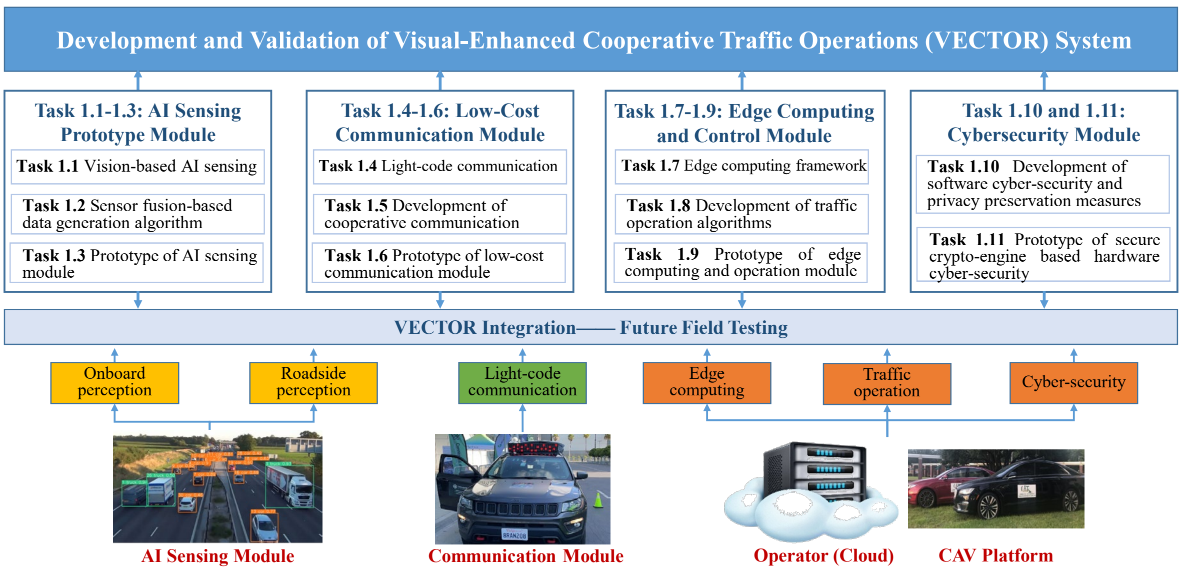


Figure II.1.12.1 The overall project architecture and task decomposition.

As shown in Figure II.1.12.2, the specific steps are as follows: Step 1 involves the collection of real velocity data from CAVs, facilitated by the group's lab. This data serves as the foundational layer for subsequent computational models and algorithms. Hybrid Lincoln MKZ vehicles are employed in the study to gather this crucial data, enriching the open-source database for further research. In Step 2, polynomial fitting techniques are applied to the collected velocity data. The data is segmented into 15-second intervals for the fitting process, with a third-degree polynomial function serving as the mathematical model. The coefficients and performance metrics of these fits, such as R-squared (R^2) and mean squared error, are meticulously recorded, demonstrating the accuracy of this method for conveying dynamic information in a simplified format. Step 3 addresses a key limitation: the restricted data capacity of light-emitting diode (LED) lights for transmitting dynamic information. To overcome this, this protocol converts the polynomial parameters into a binary sequence, which is subsequently conveyed through the flashing patterns of the LED lights. This technique allows for transferring critical dynamic information, including safety parameters like vehicle position and speed, in a constrained data environment. By sequentially following these steps, VECTOR conveys complex dynamic information between CAVs using low-cost, energy-efficient methods. This methodology can fulfill the project's objectives and provides a scalable and practical framework for broader CDA technology adoption.

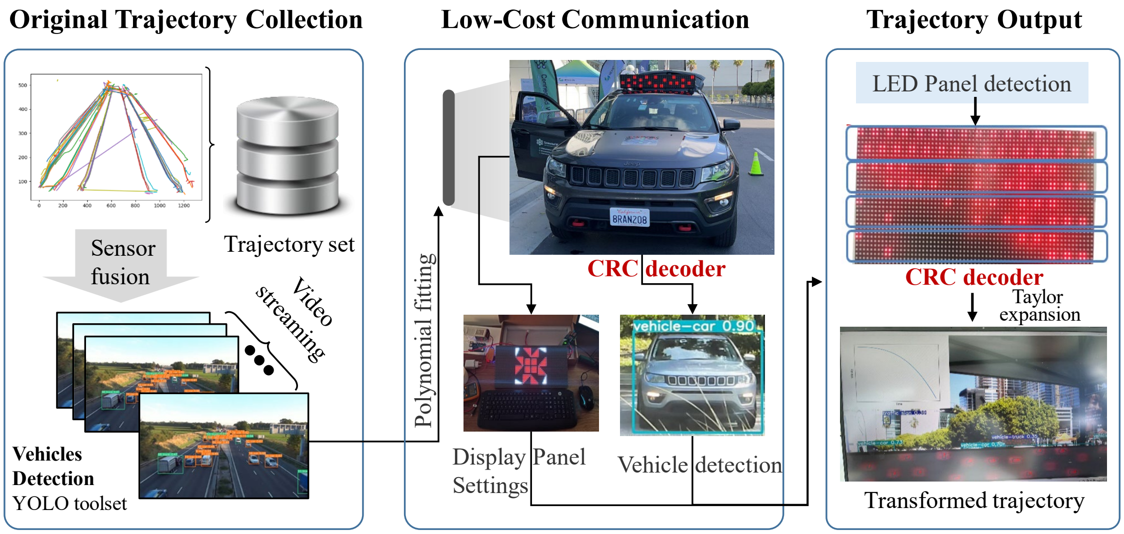


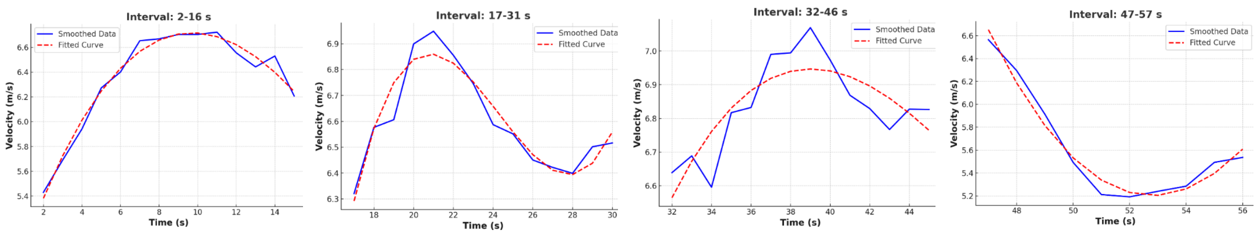
Figure II.1.12.2 The AI sensing process and low-cost communication module development.

Results

In the past year, the research group have successfully developed a vision-based AI sensing algorithm, achieving milestones in the detection of various vehicle types, vendors, and determination of CDA cooperation classes, alongside other environmental factors. This progress was marked by the successful development and validation of the AI sensing module, which showcased a high average recognition accuracy for unobstructed objects such as vehicles, pedestrians, signage, and lane markers, all within a safe sight distance and a rapid timeframe. These validations were conducted through a combination of hardware-in-the-loop simulations and small-scale field tests.

In Task 1.1, the research team enhanced the YOLO algorithm, an open-source AI toolset for vehicle trajectory extraction from roadside camera footage, achieving high detection accuracy but facing challenges in translating to real-world GPS data. By using pre-measured lane markings as references, the research group ensured adaptability. Task 1.2 developed a machine learning-based sensor fusion algorithm to improve the accuracy of vehicle trajectories from fixed location sensors. Utilizing a physics informed machine learning-based fusion algorithm, the group integrated roadside video and onboard sensor data, overcoming errors and discontinuities. This comprehensive approach, incorporating multiple data sources, ensured accuracy and reliability in vehicle trajectory data, crucial for the AI sensing algorithm's success. Building upon the achievements in Tasks 1.1 and 1.2, the research team-initiated Task 1.3, focusing on the prototype development of the AI sensing module. Leveraging existing devices, the group began implementing the previously developed algorithms, ensuring their integration and functionality in real-world settings. Additionally, the group utilized the AI sensing algorithms on a CAV testbed, enabling us to collect valuable camera video data for further analysis and refinement of the developed algorithms.

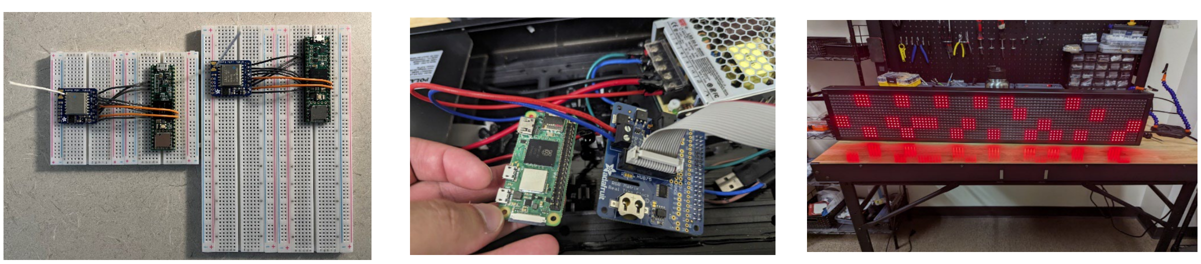
In Task 1.4, the research group is dedicated to creating a light-code communication protocol and recognition system, utilizing dynamic encoded messages and high-resolution camera video data for short-range communications. Thus, some velocity data was first collected by the connected and autonomous transportation systems laboratory (CATS Lab). One CAV follows the leading CAV. The following CAV enhances road capacity and energy efficiency by adjusting to the lead CAV's speed, achieving optimal spacing. Then, the group employed polynomial fitting to convert the original velocity data into several polynomial parameters. Notably, a CAV generates a corresponding trajectory each time based on a pre-set time parameter. In this experiment, for the sake of clarity, the group set the time parameter at 15 seconds (in a typical operation, this value would be much smaller). A third-degree polynomial function was used to fit the velocity curve in four 15-second intervals. As shown in Figure II.1.12.3, the smoothed velocities and the velocities predicted by the third-degree polynomial functions closely align for each time interval, despite the quality of the fit varying among intervals. The average R^2 is about 0.8 for these fitted velocities.



(a) (b) (c) (d)

Figure II.1.12.3 Third-degree polynomial fitting to the original velocity data in each time interval.

Then a binary matrix to represent various parameters of velocity was developed. The first line of this matrix delineates the current state of the CAV and specific characteristics of its velocity curve, utilizing a ten-digit binary code. The subsequent three lines of the matrix represent numerical values converted into binary form, detailing the coefficients of parameters. In constructing the first line, the initial four digits define the CAV's current state, such as indicating whether it is in a cruise drive at a low speed. The fifth and sixth digits represent characteristics of the CAV's velocity curve, with the fifth digit indicating the sign of the first coefficient, and the sixth digit reflecting the magnitude of this coefficient. Digits seven through ten are assigned based on additional parameters. In the following three lines, every digit is used to represent the numerical values of coefficients, converted into binary form. For instance, the number '1.67160' is transformed into its binary equivalent and displayed across these lines. By employing this comprehensive binary matrix, our team has successfully encapsulated a range of crucial information regarding the CAV's state and relevant parameters, aiding in the streamlined analysis and decision-making pertinent to CAV navigation and control.



(a) (b) (c)

Figure II.1.12.4 (a) Hardware integration. (b) A Raspberry Pi Zero 2 W alongside the Adafruit RGB Matrix Hat. (c) The LED panel displays the 'encoded-message-VECTOR' image.

Transitioning from the short-range communication endeavors in Task 1.4, the research group directed its focus to Task 1.5, aiming to develop cooperative communication using long-range (LoRa) technology. A comprehensive framework was meticulously designed, encompassing hardware integration with Teensy 3.6 and Teensy 4.1 microcontrollers connected to the RFM95 LoRa module, as illustrated in Figure II.1.12.4. A specialized Media Access Control (MAC) protocol was crafted to minimize transmission latency, supported by a rich library facilitating ID interchange and collision detection. Programming was executed within the Arduino IDE, utilizing both the Radio-Head and a custom CAV support library, ensuring rigorous testing and validation of various data metrics to meet the stringent requirements of the project. This integrative approach in Task 1.5 not only extended the communication range but also fortified the cooperative communication capabilities of autonomous vehicles, building upon the short-range successes of Task 1.4.

Following the development in Task 1.4 and 1.5, the group proceeded to an LED panel to test the VECTOR prototype in the vehicle platform as requested in Task 1.6. The following vehicle will use YOLO to extract vehicle and panel information as shown in Figure II.1.12.5 (a) and (b) which provide screenshots taken from the internal ROS system, and a drone's overhead view, respectively, during the binary communication display test. Each screenshot corresponds to one of the four-time intervals (each lasting 15 seconds).

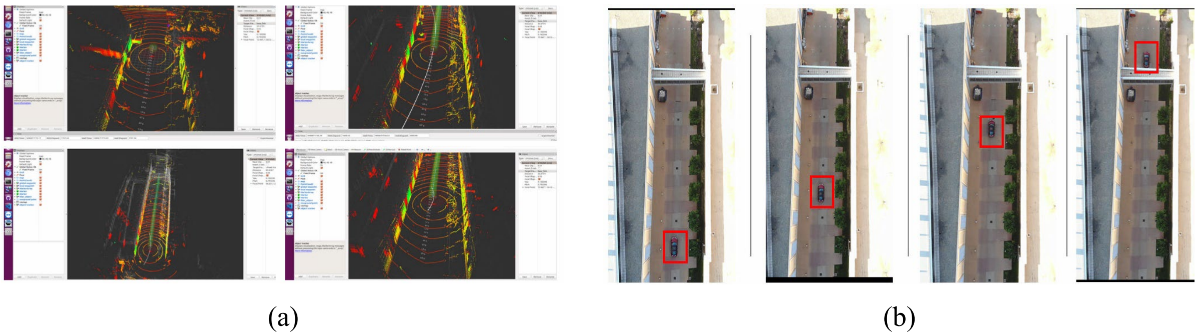


Figure II.1.12.5 CAV system illustration. (a) Screenshots of the inner ROS system. (b) Drone overhead view.

Figure II.1.12-6 shows the inner and outside view of the CAV working state. These experiments demonstrate the potential of VECTOR system for efficient and effective communication between CAVs, showcasing the potential of using binary code and LED displays to transmit dynamic vehicle information.

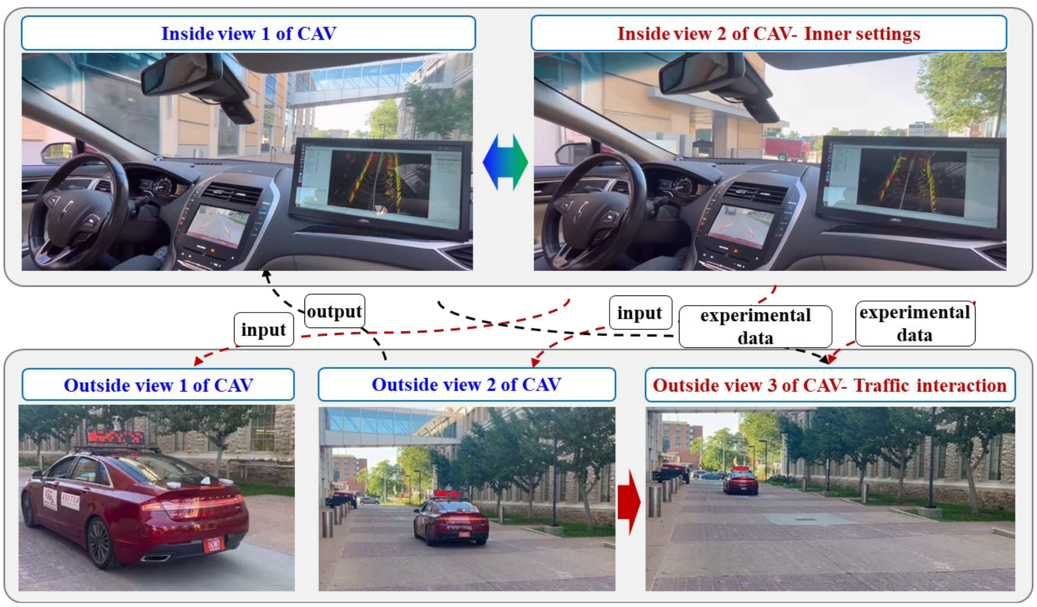


Figure II.1.12.6 Inner and outside view and data stream transmission of the CAV.

Furthermore, Tasks 1.7-1.9 develop the edge computing and control module. The research group developed traffic operation algorithms and the edge computing framework will be developed. In the traffic operation system (Task 1.8), a crucial step is to do the trajectory planning of CAVs in response to the traffic signal status. With the objective of reducing CAV energy consumptions, the so-called Eco-trajectory Planning Problem (EPP) poses even greater computational difficulties due to its nonlinear, high-order, and non-convex objective function. The team has introduced a translatable explicit predictive model control framework to address a specific issue, incorporating both offline and online modules. The offline module is responsible for generating an optimal batch of eco-trajectories, each tailored to specific initial and terminal states of a vehicle, with a focus on minimizing fuel consumption while adhering to vehicle dynamics constraints. This batch forms the basis for the online module, which conducts dynamic trajectory planning through a batch-based selection method. Depending on the situation, the online module can assign complete trajectories or generate continuous trajectory sections, ensuring smooth transitions.

In Task 1.10, the research team developed cybersecurity module for the system and investigated general privacy issues in visual enhanced vehicle control systems, simulated different adversarial behaviors from attackers' view, and validated privacy-preserving scenarios under different vehicle operations. The algorithm for edge computing has been optimized, innovating in asymmetric and heterogeneous key management, and asynchronous ciphertext processing, resulting in enhanced privacy preservation with verified security. It was proved that the encryption errors are bounded, and the optimality gap converges as the algorithm converges. The research group has crafted a crypto-engine-based hardware cybersecurity system specifically for Task 1.11, employing physically unclonable functions to generate secure cryptokeys. This innovation is pivotal for the VECTOR platform's integrity, ensuring robust protection against potential cyber-attacks. Central to various security strategies employed in the project, the cryptokey stands as the root of trust, being fundamental for data encryption and decryption, as well as for performing operations on ciphertext using homomorphic computation algorithms. To mitigate diverse vulnerabilities, including those posed by machine learning and side-channel attacks, the team has implemented advanced technologies. The hardware chip platform prioritizes the generation of a wide array of resilient cryptokeys, aiming for cost-effectiveness and ease of production in silicon. The project demonstrates the on-chip generation of cryptokeys, a crucial security measure for various applications, resulting in a highly secure cryptographic chip compatible with a Raspberry-Pi board, facilitating wireless communication in connected vehicles, and is integrated with microcontrollers connected to the RFM95 LoRa module.

Conclusions

The study confirms the potential and effectiveness of the VECTOR system as a novel means of communication for CAVs. By employing polynomial fitting, the group can efficiently convert dynamic vehicle data into binary codes, allowing for high-quality data transmission using simple LED panels. The experimental results provide convincing evidence of the system's viability in real-world scenarios, demonstrating its capacity to handle dynamic vehicle data accurately and efficiently. This methodology introduces a new layer of communication for CAVs, contributing to their safe and efficient operation. By comparing the final accuracy, this approach can achieve 90% of the original velocity data. Future work will aim at refining this system, focusing on scalability and integration with other CAV technologies, to enhance the safety and efficiency of autonomous transportation.

Key Publications

1. K. Ma, X. (S.) Li, P. Zhang, Z. Liang, T. Xu, "A Novel Vehicle-to-Vehicle Communication Approach via Binary Light Code," TRB Annual Meeting, Washington D.C., January 2024.

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2. Ke Ma, Hao Wang, Zewen Zuo, Yuxuan Hou, Xiaopeng Li, Rui Jiang. 2022. "String stability of automated vehicles based on experimental analysis of feedback delay and parasitic lag." Transportation Research Part C: Emerging Technologies.

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II.1.13 Testing and Evaluation of Curb Management and Integrated Strategies to Catalyze Market Adoption of Electric Vehicles (Los Angeles Cleantech Incubator)

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Start Date: January 1, 2023 End Date: June 30, 2024
Project Funding: $3,468,129 DOE share: $1,767,572 Non-DOE share: $1,700,557

Project Introduction

The Testing and Evaluation of Curb Management and Integrated Strategies to Catalyze Market Adoption of Electric Vehicles Project aims to study how curb management interventions can speed up the electrification of last-mile delivery and ride hailing while improving curb productivity and utilization in an effort to reduce air pollution and bring the technology to disadvantaged communities (DACs) and environmental justice (EJ) communities. The project builds on the lessons learned from the first U.S. Zero Emission Delivery Zone in the City of Santa Monica, launched in Spring 2021. In this project, the partners are working to scale zero emission delivery zones across two U.S. metropolitan areas with some of the worst air quality in the country—the Los Angeles area (focusing on the cities of Santa Monica and Los Angeles) and Pittsburgh, Pennsylvania. The partners are conducting research on curb management strategies and policies and will design pilot projects to test curb management strategies with metrics that inform and accelerate the efficiency and electrification of last-mile delivery and ride-hailing vehicles. The learnings from this research and the pilots will provide cities across the country with a roadmap for the use of curbside management as a key tool to accelerate electrification and improve efficiency and accessibility in the transportation sector.

Objectives

The objective of this project is to develop and validate open-source curb management tools and approaches, to develop a roadmap/blueprint of recommended technical, policy, behavioral incentive, and data-driven curb management strategies for cities and local governments, to ultimately achieve the following:

- Increase total urban area dedicated to zero emission curb zones by ≥50% in ≥3 locations.
- with ≥25% located in DACs and EJ areas.
- Increase EV adoption by ≥5% in conjunction with the DAC and EJ areas.
- Increase mobility energy productivity by ≥10%.
- Increase curb utilization by ≥5%.

By the completion of this project, the team aims to complete the scaling of zero emissions curb management operations for delivery and TNCs, monitored by camera computer vision, in Pittsburgh and Los Angeles. Once the curb management technology has been scaled, the data collected and results from the deployment will be tested, analyzed, and modeled to achieve ideal outcomes and optimal strategies, based on the cities' needs, to successfully achieve the objectives of the project. In addition, the project aims to develop a roadmap that can be replicated to support comparable zero emission vehicles and curb management goals in other cities and address distinctive curb management and transportation infrastructure outcomes.

Approach

In recent years, on-demand food and package delivery, as well as ride-hailing, have reshaped curb utilization dynamics. Cities are working to advance EV adoption, especially among delivery and ride-hailing drivers, to help meet zero emissions goals. Given that cities are often limited in implementing more widespread pollution and congestion pricing policies, curb management is a crucial lever for advancing these objectives. This project draws insights from multi-city experiences in Los Angeles and Pittsburgh, serving as testing grounds for modeling interventions, incorporating feedback into these models, and evaluating results to create a blueprint for policymakers and other city governments.

In order to deploy, observe and analyze interventions, testing their real-world applications, the two city regions have outlined the following approaches:

<table>
<tr><th>Los Angeles Region</th><th>Pittsburgh Region</th></tr>
<tr><td>

Partners will utilize Automotus data combined with traffic flow, network, and VMT data to examine impacts at the intervention curb locations.
The team will conduct surveys of stakeholders in the tested and controlled areas to understand motivations of decision-makers and project participants. The team will use VISUM and VISSIM traffic simulation software to develop and calibrate a microsimulation model (VISSIM) to simulate vehicle behavior at the curb and integrate curb behavior into the local traffic network.

</td><td>

Partners will utilize Automotus data to establish a sophisticated simulation model for a combined multi-modal transportation network (Mobility Data Analytics Center – Prediction, Optimization, and Simulation toolkit for Transportation Systems -MAC-POST) for Pittsburgh that will estimate mixed traffic flow and system performance.
To better understand multi-modality (vehicles, passengers) interactions and traffic flow, the team will utilize multi-modal data.

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Upon completing the development of both models, the research partners on both coasts will collaborate on opportunities for integrating modeling data and simulations that can be communicated between both the MAC-POST Model and the VISSIM/VISUM Model. If successful, this will allow both research groups to model, deploy and test interventions and scenarios that can be leveraged by both modeling systems. This integration will also enable other cities to easily adopt either system for modeling and borrow similar scenarios for their transportation modeling.

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Budget Period 2: A Focus on Systems Applications and Iterative Implementations

The related objectives include 1) completing meso- and macro-system modeling and associated impacts in order to leverage the MEP and related metrics to assess the pilots' impacts 2) develop the models in coordination with local government partners and community-based organizations to support the scale up of technology deployment and location selection, and 3) identify curb management strategies for testing. To reach these milestones for the second budget period, the project team outlined a set of tasks to accomplish in its Progress Guide, which is an adapted version of its Project Management Plan and Technical Contribution Plan.

Model Development

To ensure that all of the anticipated outcomes and metrics can be measured between each model, the project team has been coordinating with Cityfi who is developing a data framework model. The framework will work to ensure that project data collection will support necessary input measurements to evaluate results associated with the standardized and elected metrics. The data framework will 1) define necessary data feeds and services for critical metrics input measures, 2) normalize data sets to feed standardized and localized metrics, while mitigating known data gaps and limitations through the collection and data acquisition modes, and 3) provide clear project data insights through a comprehensive field and attribute level model that describes field relevance to metrics, etc.

Mesoscale & Macroscale Model Development

The University of Southern California (USC) and PNNL teams have been leading efforts for mesoscopic and microscopic modeling in downtown Los Angeles. To support this effort, they worked in collaboration with Southern California Association of Governments (SCAG) and Los Angeles DOT (LADOT) to acquire mesoscale and microscale data to build out their VISUM and VISSIM models. The West coast research team first created a mesoscopic model which takes in regional level data, which a more discreet analysis of an area which expands just beyond downtown, and then they built upon the results of the mesoscopic model to begin building a microsimulation of an area that includes the current zero emission curb zones in downtown The microsimulation model uses archived data, as LADOT's traffic and volume act as inputs to inform how traffic has changed. The group has worked to incorporate Automotus data and truck traffic data, as well as a calculated freight trip generation for the downtown study area, to ensure they are developing the simulation model with real-world data.

The Carnegie Mellon University (CMU) team has been developing and enhancing their agent-based mesoscale simulation package (MAC-POSTS) and calibration framework using high-granular multi-source data to estimate the multi-modal demand that reproduces the real-world traffic and curb usage observations. During this time period, they have been working to enhance the model with additional data collected from the installation of more smart loading zones and continue to improve the calibration of travel time.

Mobility Energy Productivity (MEP) Modeling

The NREL team has been leading work on MEP, measuring the ability to connect a person to a variety of services and activities relative to the convenience, cost, and energy associated with delivery drivers and ridehail services. For this project, MEP will be measured in relation to the curb in order to reduce cruising and make loading time more efficient. In working to determine the inputs for this metric, the project team determined that MEP is a function of curb utilization, and the teams will build off of that metric later in BP2 and 3.

Scaled Deployment Site Selection

The aim of the project team has been to scale to 218 site locations for camera installation to support automated license plate reader (ALPR) traffic enforcement in the two cities. As the City of Pittsburgh is further ahead in their policymaking, the majority of the cameras will be installed in the City of Pittsburgh (~130) with fewer (~88) being installed in the City of Los Angeles. The site locations will be determined with each city government. Those City agencies will utilize some preliminary congestion data and location selection criteria to determine best site locations.

Curb Management Scenarios Analysis

All modeling teams have agreed to coordinate on the development of scenarios to enable similar outcome comparisons between the two cities for the core metrics we are hoping to change with EV adoption. The key scenarios that will be modeled include: TNC/taxi service, delivery vehicle activities, and double-parking and will include pricing schemes for both EVs and ICE vehicles.

Installation of Scale Up Video Analytics Cameras

Installation of cameras will be predominantly supported by the Automotus team in coordination and collaboration with each of the various City departments. In the City of Pittsburgh, Automotus will work with the Department of Mobility and Infrastructure (DOMI) and the Pittsburgh Parking Authority to select locations and access permits to install cameras. When needed, the Automotus team will support policy changes, design and install signage, and conduct outreach to local businesses and BIDs. Similarly in LA, the Automotus team will work with LADOT to complete the scale up. The rate of the scale up for camera installation is dependent upon the “scaled deployment site selection” milestone as well as further adoption of ALPR policy in both cities.

Other Activities

During this budget period the project team was tasked with hosting a national workshop to bring together transportation and curb management stakeholders from the region to highlight progress and findings from DOE.

Because of the multi-city nature of the study, the team decided to host the national workshop virtually and then made plans to support a listening session for delivery drivers and ridehail groups in the two cities. This will support some of the work to gain feedback from the drivers that will utilize parking in the zones.

Results

Over the past 10 months, project partners have met numerous times to coordinate, organize, review, revise and document tasks to move towards completing the various project products and milestones for Budget Period 2. Over the past few months, the product team has run into unforeseen policy challenges that have delayed its progress and has ultimately limited the project partners from making gainful progress in completing Budget Period 2 milestones but has enabled the team to coordinate on data collection and modeling tasks. Because of this the project team applied for a no cost budget period extension of 6-months in order to enable all the teams to complete the BP2 products/milestones within the budget period with the funding available. Below are summaries of the results associated with each of the milestones that have been made thus far.

Model Development

The Cityfi Team has completed the metrics framework, to organize all desired project outcomes including process-related outcomes, project-wide required outcomes, and elective, localized outcomes. Related to the development of a comprehensive project data framework, the Cityfi Team has been applying the framework methodology to identify gaps in data inputs from both source/field data collection research team models that will be required to calculate metrics and evaluate outcomes. This has resulted in their support of identifying additional data partners to provide this missing/gap data sources relating to TNCs vehicle activity and those of delivery drivers at curb.

Mesoscale and Macroscale Model Development

The USC and PNNL teams are working to complete their model development. With additional time from the no cost budget period extension, they will be able to obtain a baseline database with not only traffic data, but also demand for delivery vehicles. To support this effort over the past 10 months, USC developed/presented model-flow and data-flow diagrams to highlight steps toward a dynamic microsimulation model. This has enabled USC and PNNL to complete the regional VISUM model and continue to develop a geographic VISSIM base model with an automated road network using signal timings provided by LADOT. In collaboration, USC and PNNL anticipated completing the mesoscopic VISUM model, to enhance and validate VISSIM scenario models earlier in the budget period. Due to needing and reviewing additional data sources, the team has now finalized the model while identifying initial data input requirements for micro-simulation modeling of the downtown area in Los Angeles (Figure II.1.13.1). Additionally, the USC and PNNL Team are working on an analysis on congestion and demand for freight that could be used to identify new zones for LADOT associated with delivery or high traffic congestion.

Figure II.1.13.1 Meso and microscale model

The CMU project team is currently calibrating the model, having conducted comprehensive analysis of the impact of smart loading zones on traffic speed in downtown Pittsburgh, including their heterogeneous effects by time of day, length, and side of the road, and having prepared written reports of the results (Figure II.1.13.2). Over the past year, they have been working to enhance the meso-scale simulation calibration with high-granular multi-source data, including Automotus curb events. They completed the model development and are now working to calibrate the model utilizing Automotus data with unique identifiers. Once this is complete, the CMU team will be able to test various scenarios within the mesoscale model with high confidence in the output of the model.

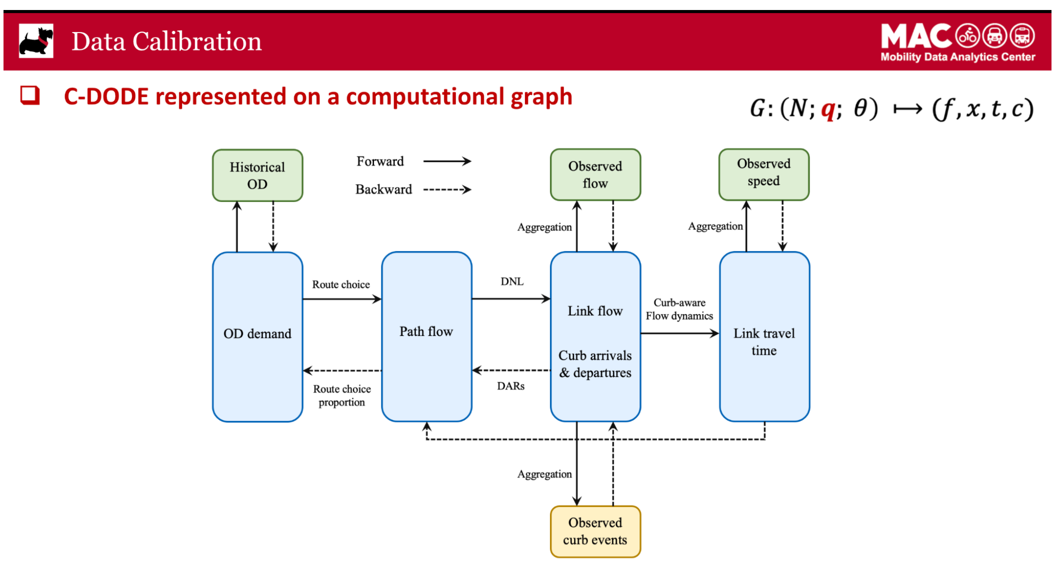

Figure II.1.13.2 Data calibration for mesoscale model

MEP Modeling

The NREL modeling team, and LACI, have both been in touch with ride hail and delivery data providers. Over the past few months this team has been working to finalize contracts to receive data that will improve the accuracy and real-world scenarios associated with ride hail driving and curb demand. This data will help the project team better leverage curb utilization to identify a MEP model for ride hail and delivery drivers. Additionally, the PNNL team has also worked to develop formulas that could support NREL's MEP model. The two labs have been working in the background to determine the best way of integrating this information as well as when and how it would be best to share with the broader team. Currently they are working to identify initial MEP-related data, methods, models, and scenarios now estimate/quantify impacts on mobility including changes in travel time (first), costs/revenue (second), energy/emissions (third), access (final).

Scaled Deployment Site Selection

In the **City of Pittsburgh**, 47 cameras will be installed before the end of December, completing about 50% of camera installation for this City. In addition to identifying more Smart Loading Zones, the City of Pittsburgh is interested in using this technology to monitor and enforce red curbs/no parking areas in its scale up to better understand negative externalities that occur as a result of the initial camera installation. The East Coast Team will benefit from additional time to identify additional Smart Loading Zones as well as red curbs that would benefit from curb management.

In **Los Angeles**, an initial phase of zero emission delivery zones was implemented throughout the city at high demand curbsides within high density neighborhoods. LADOT plans to expand the program to more neighborhoods and seeks additional insights regarding curbside demands and current congestion in the downtown area to inform their site selection for program expansion. This could be completed by the end of November; however, the budget extension will allow the PNNL and USC teams to ensure they can clearly outline LADOT's needs. Installation of Scale Up Video Analytics Cameras is dependent on-site selection and policy adoption. While interpretation of ALPR policy created delays this summer, the recent authority to pilot ALPR means that enforcement for the project in LA will likely be initiated by the end of the calendar year, allowing the team to better identify locations and provide capacity for phased installation.

Curb Management Scenarios Analysis

In several meetings, the topic of establishing curb management scenarios and later analyzing the related outcome has been discussed for both cities. In the City of Pittsburgh, the East Coast research team is confident in their ability to develop and test curb management scenarios but believe additional time will support high quality work outputs. They have initialized outlining some scenarios (i.e., different pricing and space allocation strategies) for evaluating interventions but need to finalize the plan with other research teams to compare results. In Los Angeles, the City of Los Angeles is not currently authorized to enforce ALPR bill-by-mail or directed citations and for that reason, real-world curb management cannot be tested in the model, only in hypothetical/synthetic scenarios. Additional time from the budget extension will 1) enable PNNL and USC to further their research model development and document insights of what could be done to model scenarios and 2) allow for additional time in LA for ALPR Policy to be adopted and implemented as a curb management measure. Recently, the LADOT received confirmation from its leadership team to move forward with utilizing ALPR enforcement technology in a pilot project at some capacity in the next few months. While the city government works to implement this policy change, the West Coast research team continues to collect literature on curbside and driver behavioral aspects to aid in the development of model scenarios.

Project partners will need to analyze parking data to determine what type of interventions to test with various types of parking scenarios. This could be supported through data, as shown in Figure II.1.13.3, related to curb space count and parking time duration. Currently potential interventions to consider when outlining various scenarios include:

- Monetizing curb space for various usage like pick-up/drop-off buses, freight and parking.
- Energy efficiency – designated zero emission zones for vehicle type.
- Economic/governmental monetization of the curb.
- Business oriented monetization of the curb.

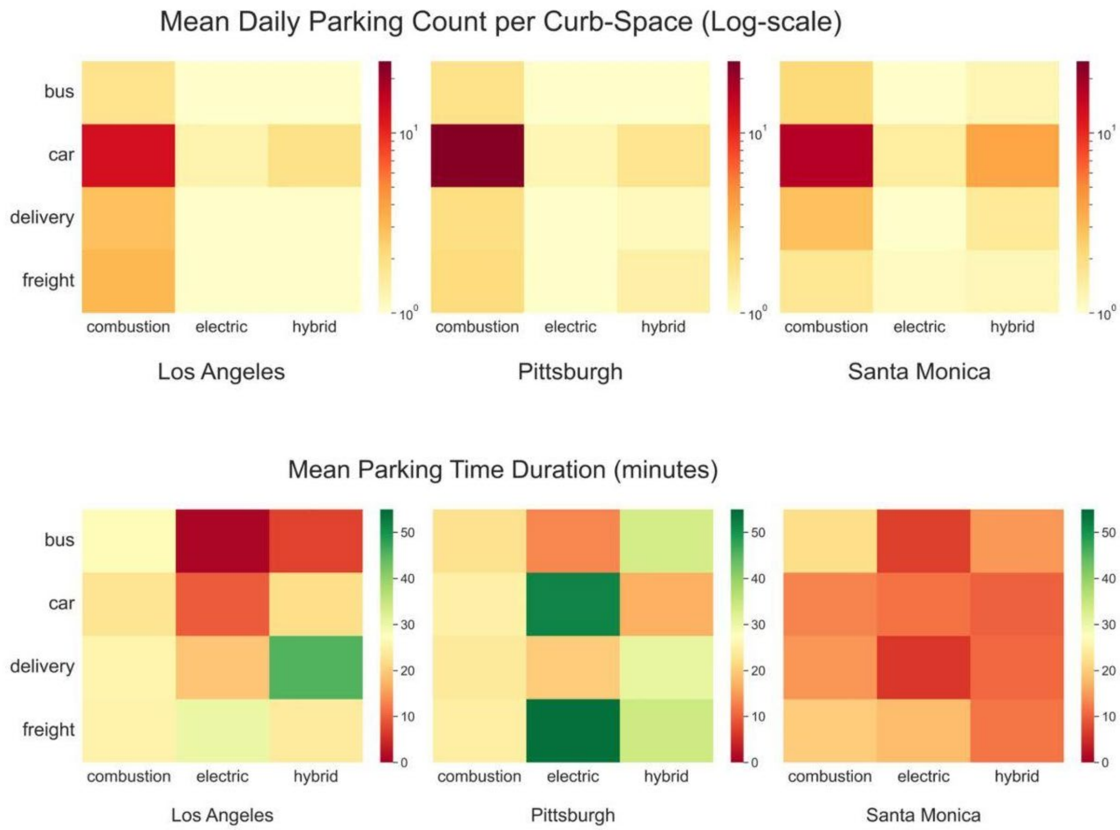

Figure II.1.13.3 Metrics from Automotus data – mean parking counts per space and mean parking times

Installation of Scale-Up Video Analytics Cameras

The project team has started a number of items here, but this milestone is dependent on finalizing site selection and the development of curb management scenarios as well as policy initiatives in the cities. The 6-month extension request will support the project partners with time to troubleshoot policy challenges faced to meet this milestone. The Automotus team has reviewed +120 new locations this past quarter with the City of Pittsburgh for potential installation for the camera scale-up in this budget period. The Pittsburgh scale-up increased installed locations by 30 before pausing due to community feedback and program changes that needed council approval. Additional areas are being considered for scale up as the City of Pittsburgh has approved the amended the policy and fee structure and is moving forward with plans to implement automated enforcement in the coming months.

In the City of Los Angeles, the LADOT team has begun a review of additional downtown locations. In the past quarter, LADOT has reviewed 20 locations with Automotus and ranked each on a scale of 1-3 for ease of installation. Three new locations were installed in October based on that review. The LADOT team continues to work closely with PNNL and USC to understand what lenses to filter site selection can support site selection, utilizing both the siting criteria and preliminary findings based on traffic congestion and high curb demand.

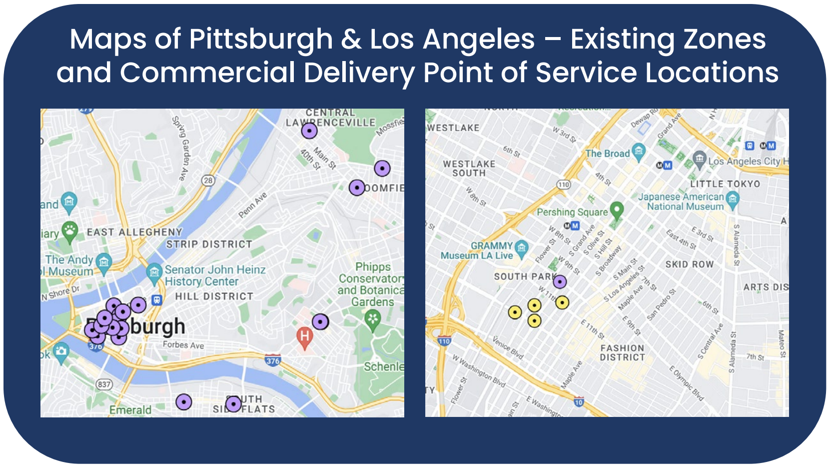

Figure II.1.13.4 Locations of smart and zero emission loading zones

Other Activities

The project team also hosted its national workshop [1] in August to share initial lessons learned from the project. The group had about 100 attendees from all over the country participate in the event and plans to hold a separate listening session in early 2024 to support learning more about the delivery driver and ridehail stakeholders. See references.

Related to the equity and communications activities in the pilot, the group connected by email and in meetings regularly to support the finalization of ridehail and delivery driver survey and its distribution to seed and initial pool of delivery drivers. The group also continues to explore opportunities to connect with driver groups as their feedback will be essential to the design portion of the project. In the remainder of Budget Period 2 the Equity and Communications Team will reconnect on a plan for 2024 and how we can bring the two groups together to expand our outreach to delivery drivers.

Conclusions

With six additional months of an extension to the budget period, project partners are working to cross the finish line on a number of interdependent milestones. While the project team has experienced a number of policy challenges and unforeseen delays, the group remains confident that all BP2 milestones will be completed by June 2024. Over the remaining 8 months of the budget period, the project team will need to prioritize camera site selection and installation scale up as well as outline curb management scenarios and interventions to test.

Key Publications

1. Kelly Gregg et al. “Cutting Across the Curb – a multi-perspective discussion on urban curb management.”

2. Giuliano, G., Binder, R., Ha, J., Amatya, V. Nicosia, Cyprus, “Curb Management for More Efficient Deliveries and EV Adoption,” June 2023.

3. Jiachao Liu a, Wei Ma b, Sean Qian a c, “Optimal curbside pricing for managing ride-hailing pick-ups and drop-offs,” January 2023.

References

1. Los Angeles Cleantech Incubator, “Accelerating EV Adoption with Curb Management Strategies”

Acknowledgement

We would like to acknowledge all partners in the first year of the project: DOE, Automotus, Inc, Carnegie Mellon University, NREL, PNNL, Southern California Association of Governments (SCAG), USC METRANS Transportation Center, City of Los Angeles, City of Pittsburgh DOMI, City of Santa Monica, Cityfi, Itron, Lawrenceville Corporation, Oakland Business Improvement District, Pittsburgh Downtown Partnership, Pittsburgh Parking Authority, and Downtown Santa Monica

II.1.14 AI-Based Mobility Monitoring System and Analytics Demonstration Pilot (University of California, Irvine)

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Start Date: October 1, 2021 End Date: December 31, 2024
Project Funding: $6,000,000 DOE share: $3,000,000 Non-DOE share: $3,000,000

Project Introduction

The development of CDA technologies has seen steady growth since the turn of the 21st century with cellular communications providing ever-increasing vehicle telematics capabilities in parallel with the concurrent development of direct V2I and V2V technologies (collectively known as V2X) focused originally on the DSRC standard. More recent developments are built upon competing or compatible standards including cellular V2X and 5G cellular technologies.

Studies show that traffic coordination based on reliable data and analytics can improve energy efficiency, traffic efficiency, and air quality by reducing congestion between 20% to 30% and emissions between 5% to 15% while improving safety [1]. An emerging CDA technology, an "AI-System" comprised of an automated mobility monitoring lidar technology mounted in an intersection network and coupled with data analytics, has the potential to generate the portfolio of backbone traffic data needed to meet the energy efficiency, traffic efficiency, safety, congestion, and economic goals to which cities aspire.

The project includes the demonstration and evaluation of an AI-System technology on a Public Road Network Platform in a real-world system application using a state-of-the-art lidar-based technology supplied by Velodyne Lidar and Bluecity Technology. The *Public Road Network Platform* is an urban roadway matrix sufficient for testing connected and autonomous vehicle technologies now and in the future, and equipped with infrastructure sensors and analytics to 1) monitor and analyze traffic in real-time, 2) provide control signals to traffic lights, and 3) inform connected vehicles.

Objectives

The goal of the project is to establish a *Public Road Network Platform* for 1) the assessment of an innovative energy efficient mobility backbone technology in a real-world transportation system; 2) the provision of needed insight into key use cases of AI-based systems to meet DOE goals including MEP and vehicle energy efficiency; (3) the quantification of system-level impact of the AI-based system technology at multiple scales; and (4) the provision of data and results to National Laboratories, EEMS researchers, and the Clean Cities/Technology Integration network. To accomplish this goal, seven objectives will be met: 1) outfit the three vehicle fleets and *Public Road Network Platform*; 2) establish the CDA simulation; 3) characterize the vehicles using software- and hardware-in-the-loop (XIL) experiments; 4) establish and test the use cases; 5) assess the technology and assure an energy efficiency improvement of at least 15%; 6) format and provide data and results to ANL, EEMS researchers, and the Clean Cities/Technology Integration network; and 7) through outreach, publications, and reports, communicate the results to the broader transportation community.

Expected outcomes of the project include a demonstrated energy efficiency improvement up to 15%; similar traffic efficiency improvements; and a demonstrable improvement of safety for drivers, pedestrians, cyclists, and the like with fewer near-misses and traffic conflicts. Through completion of the project, the transportation community will have a better understanding of how to place the AI-based infrastructure, use cases, and effectiveness in meeting goals for mobility, energy, and safety.

Approach

Budget Period 1: A portfolio of controlled traffic events (CTEs) will be developed to demonstrate the capability of the proposed AI-based system and CDA-enabled vehicles will be developed. Vehicles will then be simulated performing these CTEs and the resulting impacts will be analyzed to ensure at least a 15% improvement in energy efficiency is achievable. Locations for 25 AI-based systems will be analyzed and selected to satisfy project needs. The three fleets (individual-use, shared-use, and Mobility as a Service) will be prepared along with data logging and connectivity technologies. The XIL experimental setup will be prepared to enable simulation of CTEs to connect to and receive feedback.

Budget Period 2: The recipient will install and commission the 25 AI-based units throughout the project's *Public Road Network Platform*. XIL experiments of vehicles performing the portfolio of CTEs will be conducted and the results of these experiments will be analyzed to ensure at least a 15% improvement in energy efficiency is achievable. Lastly, the three vehicle fleets will be deployed, and data collection will begin with the reference case of Free Driving.

Budget Period 3: The recipient will perform the portfolio of CTEs. Data from the deployment including Free Driving and CTEs will be analyzed to ensure at least a 15% improvement in energy efficiency is achievable. The energy efficiency, traffic efficiency, and emissions data will be compared to those of the simulation and XIL experiments. The recipient will then scale up the data to gather insight for a hypothetical deployment at metropolitan region scale through agent-based modeling.

Results

AI-Based System Installation and Commissioning

During this Budget Period 2 reporting period, the final 20 AI-Systems were installed, completing the installation process of the 25-intersection *Public Road Network Platform*. Of the 25 intersections, 12 are currently online and recording traffic analytics (the remaining will be by the end of BP2 including traffic counts, average speed, near misses, and signal coordination. One AI-System on the Platform with its lidar sensor and edge box processor is depicted in Figure II.1.14.1. Three API calls are available: 1) object detection and classification (e.g., passenger vehicle, pedestrian, cyclist), 2) virtual traffic loop occupancy, and (3) traffic signal light status. A fourth API call is being developed by Ouster Bluecity which includes the time to signal change which allows for both 1) direct alert to drivers to plan approach to the upcoming intersection appropriately and 2) input into an algorithm which can suggest an eco-approach maneuver.

Figure II.1.14.1 Installation of AI-System at intersection of Culver Drive and University Dive.

Two examples of AI-System data are presented in Figure II.1.14.2 for (a) traffic signal arrival patterns which suggests how signal timing might allow additional traffic through with green time extensions and (b) a heat map of near misses which can be configured to focus on specific road user categories (e.g., passenger vehicle, bus, pedestrian, cyclist), vary the sensitivity in terms of time gap between two road users, and set speed boundaries.

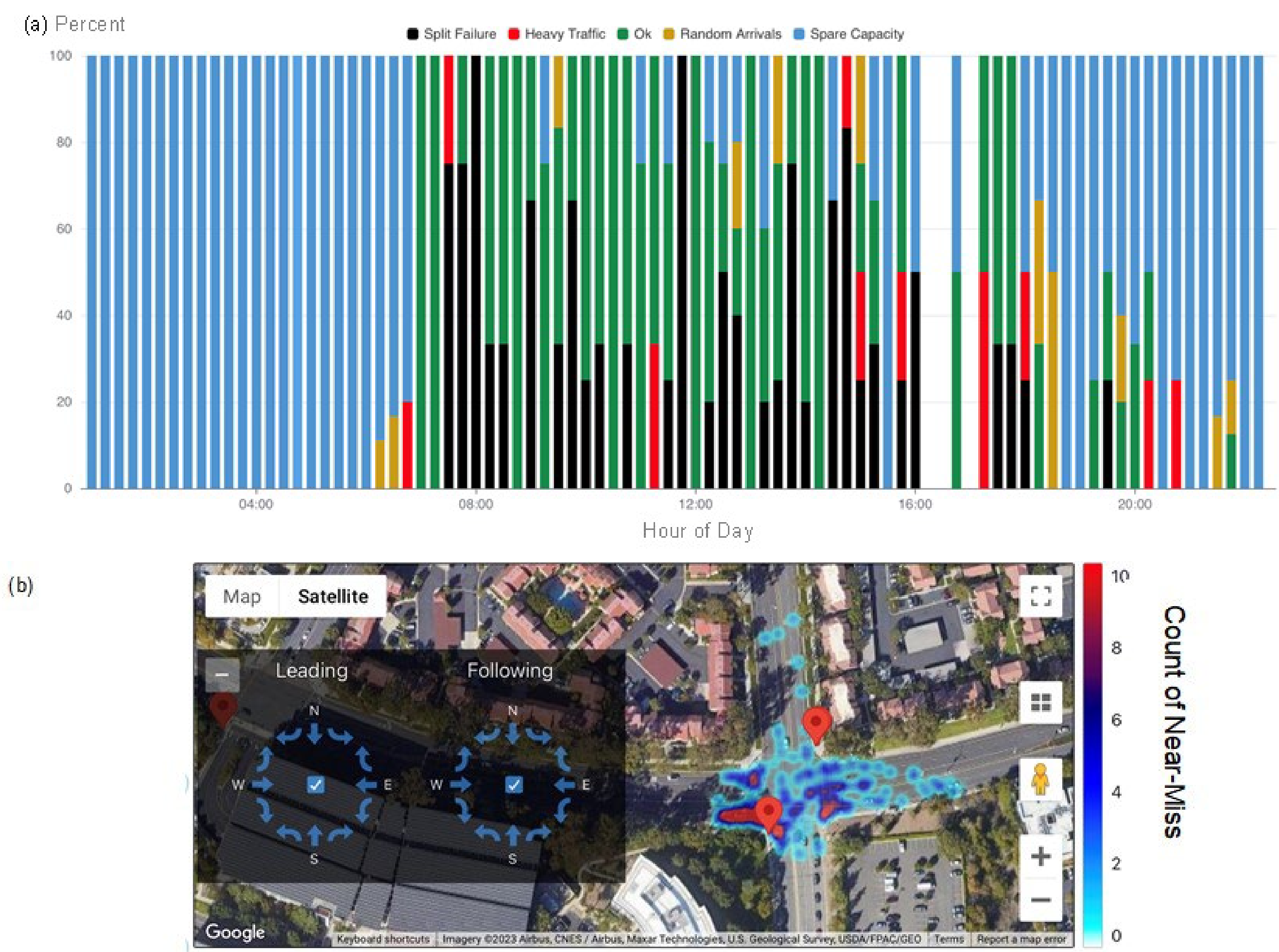

Figure II.1.14.2. AI-System traffic data: (a) traffic signal arrival patterns and (b) intersection heat map of near-misses

XIL Experiments of Controlled Traffic Events

In the first budget period, the portfolio of CTEs was designed and tested in simulation with the AI-System deploying a vehicle and signal controller from Sun et al. [2]. In Budget Period 2, additional variations of these CTEs were simulated in an expanded corridor of two intersections composed by three interlinked ring roads. Energy efficiency of each vehicle was modeled in FASTSim using the existing 2016 Nissan Leaf 24 kWh BEV which was the closest existing match to the vehicle under test [3], and the fleetwide energy and traffic efficiency impacts were analyzed. A subset of these simulated scenarios was tested in XIL configuration by ANL using one of the fleets deployed on the *Public Road Network Platform*, a 2012 Scion EV as depicted in Figure II.1.14.3. A robot driver connected to a dSPACE MicroAutoBox III controlled the acceleration and braking of the vehicle because this vehicle is not drive-by-wire capable.

Figure II.1.14.3. Scion iQ EV at ANL for XIL testing

A series several hundred simulations were conducted with variations on traffic count, free flow speed, vehicle control speed at an intersection, AI-System action distance, and the AI-System controller activation state (i.e., not active, vehicle controller, signal controller, and vehicle and signal controller). For all scenarios with the vehicle controller active, it was assumed that all vehicles simulated were connected and the drivers followed the suggested speed perfectly (this can also be assumed to represent a well-functioning connected and autonomous vehicle). A summary of simulated fleetwide energy impacts of the vehicle controller is presented in Figure II.1.14.4. It is clear from these simulation results that greater AI-System action distance (i.e., having high-resolution lidar with accurate object detection) has a substantial impact on performance. Simulations show many scenarios of vehicle controller active with simulated fleetwide energy efficiency improvement in excess of 15%, the target for this project, while simultaneously improving traffic efficiency (i.e., average speed) generally to a greater extent. Further energy efficiency improvement is found with both the vehicle and signal controllers active, with the peak at 36% decrease in fleetwide fuel consumption.

When tested in XIL with the Scion iQ EV, similar improvements were found in the subset of traffic tested. In each of the 12 scenarios, three vehicles were selected: the vehicle with energy efficiency closest to the fleetwide average, the vehicle with the highest fuel consumption, and the vehicle with the lowest fuel consumption. A summary of results from the vehicle and signal controller active scenarios is presented in Table II.1.14.1.

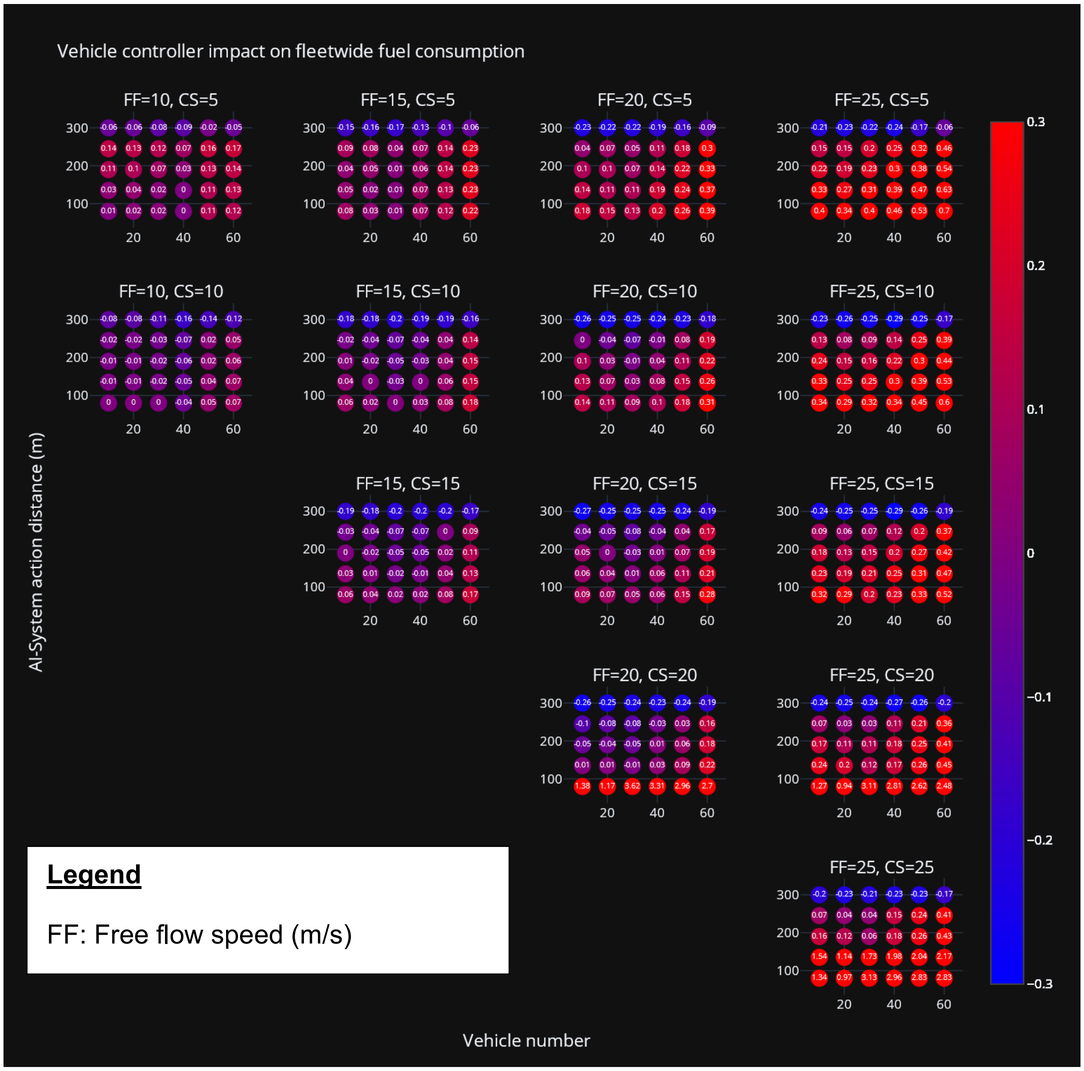

Figure II.1.14.4. Simulated vehicle controller impact on fleetwide fuel consumption

Table II.1.14.1 XiL Results of Energy and Traffic Efficiency Impacts of Vehicle and Signal Controller

AI-System Activation	Simulation Fuel Consumption (kWh/mi)	XiL Fuel Consumption (kWh/mi)	Simulation Fleetwide Average Speed (m/s)
No Controller	Average: 0.284 Min FC: 0.251 Max FC: 0.414	Average: 0.243 Min FC: 0.211 Max FC: 0.320	8.89
Vehicle and Signal Controller Control Speed: 15 m/s	Average: 0.175 (-38.5%) Min FC: 0.172 (-31.7%) Max FC: 0.248 (-40.0%)	Average: 0.158 (-35.2%) Min FC: 0.153 (-27.7%) Max FC: 0.213 (-33.6%)	12.5 (+40.6%)
Vehicle and Signal Controller Control Speed: 20 m/s	Average: 0.175 (-38.4%) Min FC: 0.171 (-31.7%) Max FC: 0.251 (-39.3%)	Average: 0.155 (-36.1%) Min FC: 0.152 (-28.3%) Max FC: 0.215 (-32.7%)	12.8 (+44.0%)
Vehicle and Signal Controller Control Speed: 10 m/s	Average: 0.177 (-37.7%) Min FC: 0.172 (-31.6%) Max FC: 0.256 (-38.2%)	Average: 0.158 (-35.2%) Min FC: 0.152 (-28.0%) Max FC: 0.226 (-29.4%)	11.9 (+33.9%)

Deploy Vehicle Fleets

Two vehicle fleets have been deployed on the *Public Road Network Platform*, the "personal-use" fleet of four KIA EV6s and the "shared-use" fleet of ten Scion iQ EVs. Each fleet travels throughout the *Platform* and data are being collected by the AI-Systems. The personal-use fleet is driven by a small group of drivers who regularly (nearly daily) drive the vehicle and therefore are familiar with the vehicle. The shared-use vehicles are driven by a larger group of drivers and are only driven on occasion when reserved. The expectation is these two structures will provide a variety of data when drivers are presented with eco-driving information.

Outreach and Education

Meetings are held monthly with Saddleback Community College on outreach and education to enable the future workforce to work on CDA technologies. A second guest lecture on CDA and zero emission vehicles was presented to Saddleback by automotive and environmental science students, and a third is planned for 2023Q4. We also participated in a curriculum advisory committee meeting which included Saddleback faculty and staff as well as automotive industry partners of the Saddleback program. This meeting focused on the trajectory of Saddleback Community College's curriculum and the manner by which each partner can provide input on the evolution of the industry and workforce needs.

The SCAG, a regional manager of the Clean Cities program, and UCI HIMaC^2 hosted a listening session on 24 April 2023. A total of 25 participants attended, including two from UCI HIMaC^2 and eight from SCAG. Other participants were from the California Department of Transportation, San Diego Association of Governments, City of Irvine, City of Los Angeles, City of San Clemente, Orange County Transportation Authority, and two community planning and advising companies. The following are highlights from the listening session:

1. Several attendees had heard of lidar technology but were not aware of this deployment.
2. Inability for profiling humans is attractive.
3. Potential to improve signal timing is attractive.
4. Interested in automating traffic enforcement/tickets.
5. Desire to warn drivers about vulnerable road users, being careful not to have drivers rely on this.
6. There is a need for standardization ultimately.

Conclusions

The key conclusion is the AI-System exceeds the 15% energy efficiency improvement target for the representative fleet tested in XIL with a battery electric vehicle, while also improving traffic efficiency (i.e., average speed) for the entire simulated fleet. This is demonstrated for a variety of scenarios with varying traffic densities and free flow speeds. Generally, a greater improvement in energy efficiency and traffic efficiency is enabled through a greater AI-System detection distance, suggesting focus should be placed on strategic placement, improving object detection, and developing lidar sensors with greater resolution.

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II.1.15 Cooperative Traffic Signal Network for Freight Energy Efficiency (Xtelligent)

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Start Date: December 17, 2021 End Date: December 31, 2024
Project Funding: $2,376,439 DOE share: $1,224,123 Non-DOE share: $1,224,123

Project Introduction

98% of signalized intersections in the U.S. today are controlled by simple timing plans and can neither communicate with vehicles nor adaptively adjust their timing based on real-time traffic conditions and needs. This significant inefficiency has resulted in unnecessary stop-and-go traffic that costs the U.S. more than $151 billion dollars per year, which includes significant energy and environmental costs. Xtelligent, a Cooperative Intelligent Transportation System (C-ITS) venture, was founded to address these challenges. Since 2016, Xtelligent has been developing the next generation ATCS technology that can optimize network flow of vehicles and other multimodal agents using signal control algorithms inspired by telecommunications networking theory. At the core of the technology are Proportionally Fair (PF) algorithms originally developed by our team members and affiliates at the MIT and USC with funding from the National Science Foundation, U.S. DOT, and California Department of Transportation (Caltrans).

We have been developing PF algorithms to determine real-time splits, offsets, and cycle time for signalized intersections to optimize network level objectives such as traffic throughput, energy consumption, and GHG emissions reduction. Traditional approaches typically use a combination of myopic intersection-level optimization and ad hoc techniques for coordination between intersections. They fail to distinguish between freight vehicles and regular vehicles. On the other hand, our approach solves the problem at the mobility systems level, encouraging coordination and preparing the systems level ground rules for CAVs of the future. A major thrust in our efforts is to make these algorithms and connectivity between vehicles and traffic signal infrastructure scalable and applicable to different types of vehicles, with a particular focus on freight vehicles. For this purpose, we adapt tools from congestion control and distribution optimization to the traffic management settings. We have also built-up knowledge, expertise, and software/hardware technology to deploy innovative control algorithms in real-life environments, most recently through DOE SBIR Phase I/II funding.

For this proposal, Xtelligent has teamed up with the NREL and the University of California, Riverside (UCR). NREL will provide MEP, freight mobility energy productivity (F-MEP), and FASTSim technical and integration support, so that the data generated from the real-life demonstration can be applied to MEP/F-MEP and FASTSim for mobility energy productivity as well as energy efficiency and GHG impact analysis. NREL will work closely with Xtelligent to integrate these tools onto the Xtelligent platform, so that these tools can be scaled, resulting in greater transparency and accountability of utilizing C-ITS technology. UCR has deep expertise in CAV testing and demonstrations and has experience working closely with the Volvo Group concerning connected eco-driving applications. UCR will deploy these applications in conjunction with the ATCS technology to further enhance the performance of mobility systems by optimizing speed profiles of CAVs. We are also partnering with three innovative California cities (Fremont, Long Beach, Ontario) that represent prototypical freight cities--all three are positioned along some of the most freight congested corridors in the U.S. and will provide a "living lab" for the demonstration along selected areas within each of these cities that are close to mobility and freight hubs, freeways, and warehouses that see significant fluctuation in travel demand. Long Beach is also a "Clean City" and will play a critical role in sharing lessons learned with the rest of the Clean City Coalition. Key automotive OEMs that are at the forefront of connected vehicle research and development (Daimler, the Volvo Group, and the Ford Motor Company) with whom Xtelligent has multiple years of working relationship will provide CAVs, data, and/or technical guidance.

Objectives

The objective of this project is to test within freight setting ATCS technology that Xtelligent has developed with DOE SBIR Phase I and II funding to optimize network flow of vehicles and other multimodal agents using signal control algorithms. The project team believes that the technology has the potential to accomplishing the following goals in the proposed demonstration areas:

Mobility Goals

1. 10%+ in travel time reduction for freight.
2. 20%+ in travel time reduction for broader mobility system.
3. 20%+ in road network capacity gains.

Energy Efficiency Goals

1. 10%+ energy efficiency gains for freight vehicles.
2. 20%+ in vehicle energy efficiency gains for the broader mobility system.

Air Quality Goals

1. 10%+ reduction in greenhouse gas emissions from freight vehicles.
2. 10%+ reduction in community exposure to pollutant emissions from freight vehicle.

The project team's ATCS work from DOE SBIR Phase I and II demonstrated 30% improvement in average speed, 23% improvement in travel time, and 5-6% improvement in vehicle pollution and greenhouse gas reduction (from travel time improvement alone, not including stop-and-go, idling, and eco-driving impact) in real-life deployment areas in California and Colorado, per the Argonne National Laboratory evaluation. With DOE VTO research funding, we will apply the learnings and technologies developed for freight application in selected locations that have significant freight movement.

Approach

To achieve the research objectives listed above, Xtelligent and its partners identified a set of demonstration site partners. These transportation agencies needed to have 1) sufficient density of traffic flow, 2) NTCIP-compliant controllers for ease of implementation, 3) at least 10-100 contiguous intersections, and 4) an enthusiastic and innovation-minded set of public works/transportation staff willing to partner on this effort. The City of Long Beach, California; City of Fremont, California; and City of Ontario, California, were selected as sites (Figure II.1.15.1). All three are well recognized freight corridors. The City of Long Beach and City of Ontario are nodes within the Southern California freight corridor that represent approximately 40% of all incoming freight into the U.S. that gets distributed into every single congressional district in the U.S. City of Fremont, California, is the home of the Tesla manufacturing facility and sees significant freight movement as result.

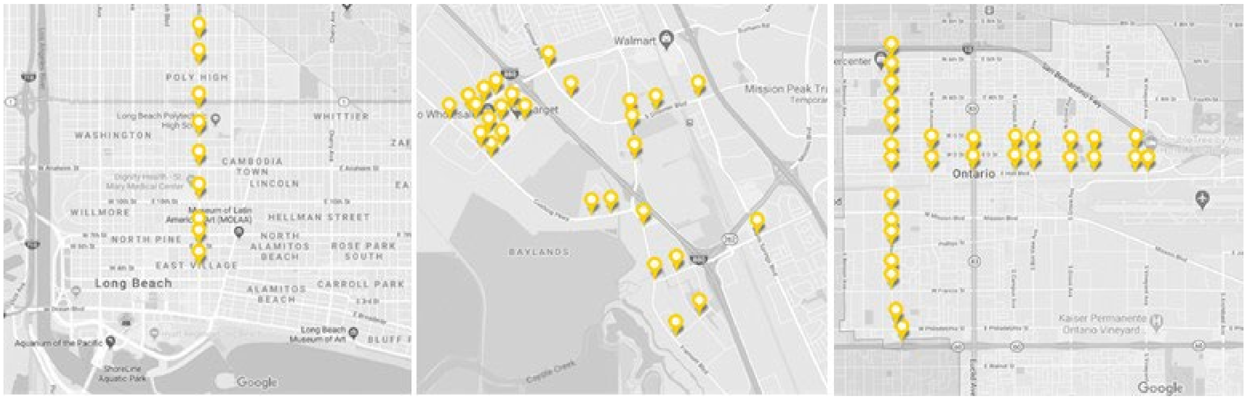

Figure II.1.15.1 From left to right: deployment sites in Long Beach, Fremont, and Ontario, California

The project is being conducted in three budget periods:

Budget Period 1: Development, System Integration, and Deployment: The team has been developing a ***Cooperative Intelligent Transportation System (C-ITS)*** operating with high-definition freight connected vehicles (CVs) that are deployed across freight hubs and the integration of freight CVs that can both send high-definition vehicle profile data (location, speed, direction, payload, propulsion type, etc.) and receive Signal Phase and Timing SPaT data for eco-driving and other vehicle control purposes.

Budget Period 2: Data Collection and Processing: The project team will collect processed data from both real-world implementations and simulation studies, covering vehicles and associated infrastructure equipped with (environmentally-focused) CV technologies in “living labs” under a variety of scenarios (e.g., congestion levels, time of day, seasons, planned/unplanned events).

Budget Period 3: Model Implementation and Energy Impact Evaluation: The project team will implement performance measuring tools such as MEP, F-MEP. The anticipated results will include the estimated impact factors on energy intensity due to the introduction of a set of freight CV technologies and C-ITS technologies, individually and/or in combination, under various scenarios.

Results

This annual progress report represents the conclusion of the second 12 months out of a 39-month period of performance under this grant. A significant amount of work has been completed to implement a real-world, in-street ATCS system to research and develop Xtelligent PF ATCS within the freight context, and months of data from deployment sites have been collected for analysis. There have been some unforeseen challenges due to legacy infrastructure that turned out to be incompatible with the project team’s planned approach, so additional engineering efforts continue to be expanded to create alternate deployment and integration solutions. Due to such unforeseen costs, the project team has been focusing its resources on Long Beach and Fremont project sites. After integration, connected vehicle data from Mercedes-Benz/Daimler R&D fleet and Dependable Highway Express (DHE) freight fleet were found to be either too sparse (since only 30-100 vehicles are operating throughout the region at any given day and these vehicles may not be traversing through the project site frequently enough) or too latent. The project team has been addressing the sample size challenge by securing access to Mercedes-Benz/Daimler production vehicles starting late 2023/early 2024. The project team has also pivoted to utilizing a smart-phone-based beacon app leveraging Ford’s SmartDeviceLink for DHE’s heavy-duty freight fleets, also providing more control for testing and data collection purposes. The integration of CV data with the control algorithm requires additional work to make it work seamlessly. Despite the various unforeseen challenges and on-going engineering refinement work to be completed, the data analysis already indicates 11.1% flush-time improvement for the most congested phase on Atlantic Avenue in Long Beach. This is a precursor metric that bodes well for the project team achieving its freight travel time reduction, broader mobility system travel time reduction, and road network capacity gain goals. UCR analysis is also pointing to material improvement in average speed, which is a strong driver for $PM_{2.5}$ emissions, when even just a few intersections are activated and even without the benefit of connected vehicle data.

The untimely deaths of two critical project team members (public works director of Long Beach and Daimler/Mercedes-Benz data engineer assigned to the project) and the war in Ukraine displacing critical Xtelligent engineering support posed additional challenges. But the project team was able to identify other team members within Long Beach and Mercedes-Benz/Daimler organizations with whom we can collaborate. The team also secured additional communication hardware and batteries to enable our engineering support in Ukraine to work with fewer disruption. COVID also continues to limit the team’s ability to interface with city staff due to continued remote working by city staff, and traffic patterns remaining unpredictable. To minimize the impact of post-COVID traffic pattern unpredictability on testing results, the project team has been collecting baseline and activation data on a near simultaneous basis instead of taking a more of a serial approach.

In sum, the project team continues to make steady progress and has made appropriate pivots to mitigate navigate around the unforeseen challenges it has faced. The project team has already achieved the Budget Period 2 go/no-go milestone of starting to deliver CV trajectory data set that meets NREL/UCR modeling requirements for MEP/F-MEP and Environmental Impact Analysis. We will be working closely with UCR and NREL in the coming months to continue refining the data pipeline, refine the signal control algorithm, improve the efficacy of connected vehicle in informing signal control, all towards maximizing the chances of successful C-ITS implementation and modeling efforts outlined for Budget Period 3.

Specific details lined up against project plans for Budget Period 2 are below.

Budget Period 2

Task 2.1 – Data Collection from Real-World Baseline Conditions:

Subtask 2.1.1 – The project team has been collecting data without activating the system to establish a baseline using field data from ATCS (Figure II.1.15.2 and Figure II.1.15.3). This has been on-going in Long Beach and Fremont on Monday/Wednesday and Tuesday/Wednesday on alternating weeks. This data is being shared with UCR and NREL for the preparation of the air quality impact model and the integration of F-MEP.

Subtask 2.1.2 – The project team has been collecting data without activating the system to establish a baseline using field data from CAVs. Three different forms of data are being generated. First, data from 30-50 Daimler/Mercedes-Benz R&D connected vehicles have been flowing onto the Xtelligent platform. In the coming months production vehicle data is expected to be provided as well. Second, heavy-duty freight fleet data from DHE (Volvo Group customer) is being provisioned through DHE’s Samsara platform. The data was unfortunately found to have high latency, so the project team has instead decided to pivot towards using a beacon app, which the driver will activate while driving. Third, Xtelligent has developed the aforementioned beacon app (leveraging know-how from Ford’s SmartDeviceLink) to turn vehicles into connected vehicles. A database has been created to collect this data.

Figure II.1.15.2 (Source: Xtelligent): Clockwise from top left; project team validating the accuracy of the streaming traffic signal data in Long Beach by comparing actual signal timing with the UI/UX dashboard; all hands meeting in April 2023 to discuss various project objectives, tasks, and progress for Budget Period 2

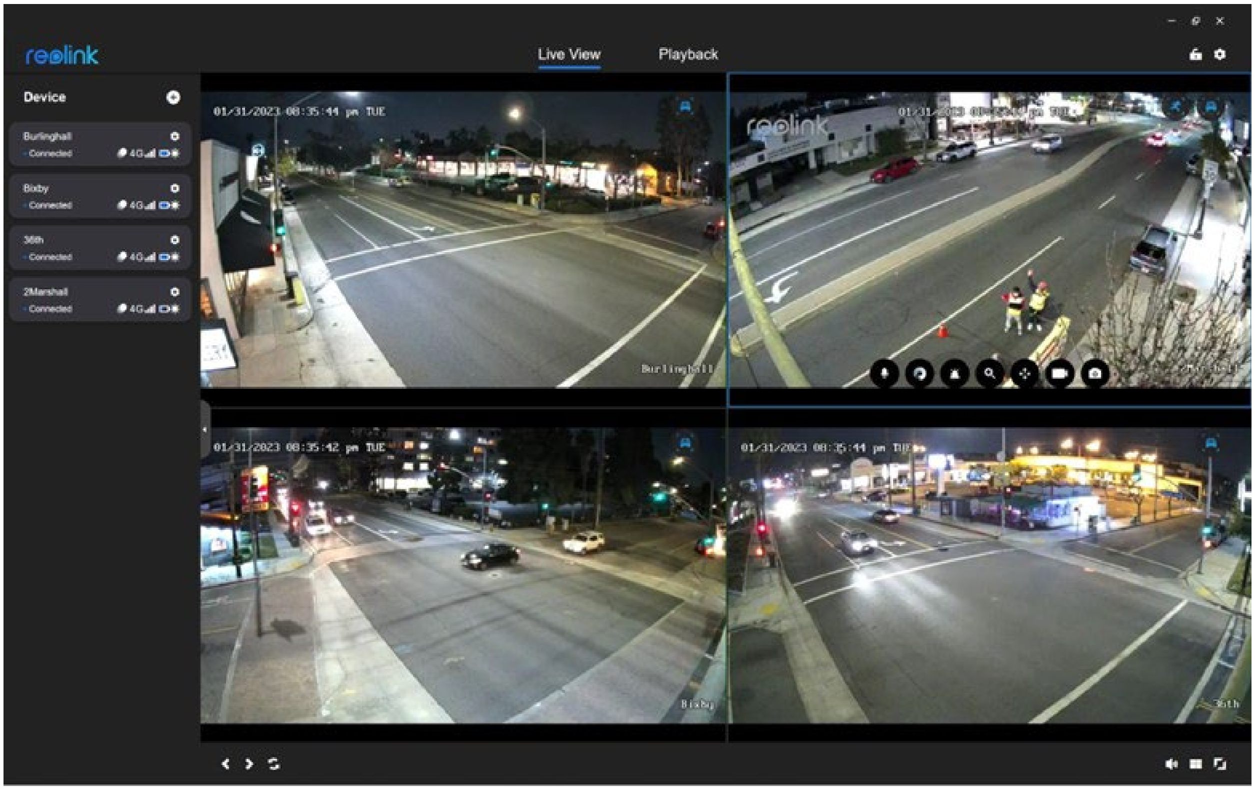

Figure II.1.15.3 (Source: Xtelligent): Project team testing video camera in Long Beach in preparation for data collection and data quality validation. Note the staff in the top right screen.

Task 2.2 – Data Collection from Real-World Baseline Conditions (with Traffic Signal Timing Optimized):

Subtask 2.2.1 – The project team has been collecting data while optimizing traffic signal timing to establish a baseline using field data from ATCS. This has been on-going in Long Beach and Fremont on Monday/Wednesday and Tuesday/Wednesday on alternating weeks. This data is being shared with UCR and NREL for the preparation of the air quality impact model and the integration of F-MEP.

Subtask 2.2.2 – The project team has been collecting data while optimizing traffic signal timing to establish a baseline using field data from CAVs (Figure II.1.15.4, Figure II.1.15.5, Figure II.1.15.6). Three different forms of data are being generated. First, data from 30-50 Daimler/Mercedes-Benz R&D connected vehicles have been flowing onto the Xtelligent platform. In the coming months production vehicle data is expected to be provided as well. Second, heavy-duty freight fleet data from DHE (Volvo Group customer) is being provisioned through DHE's Samsara platform (Figure II.1.15.7). Third, Xtelligent has developed a beacon app (utilizing knowledge of Smart Device Link from the Ford Motor Company) to turn Ford and other vehicles into connected vehicles. Due to high latency found in DHE's Samsara platform the project team has pivoted towards using the beacon app. A database has been created to collect the above data.

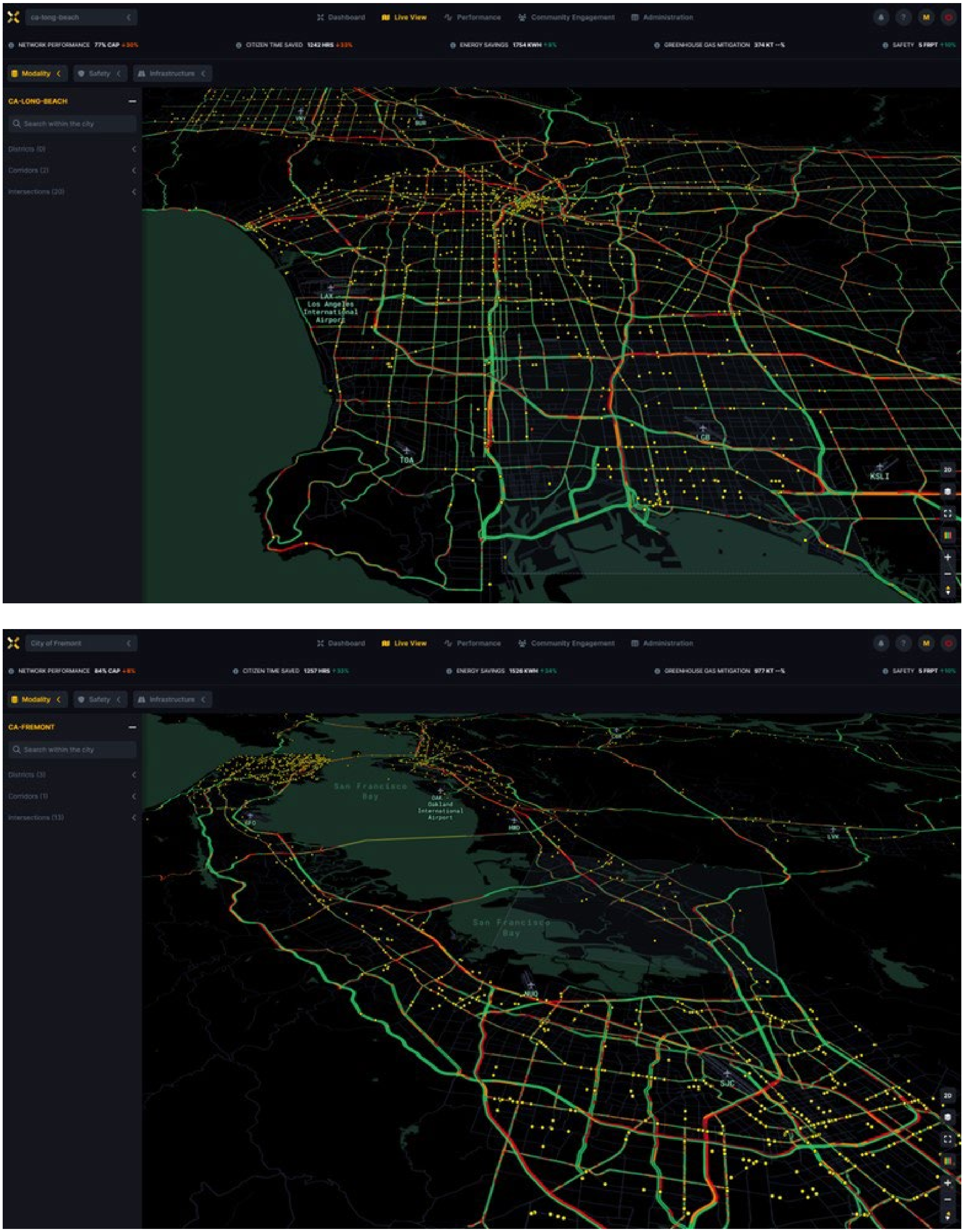

Figure II.1.15.4 (Source: Xtelligent): Streaming connected vehicle data in the broader LA region (upper image) and San Francisco Bay Area (lower image) where Long Beach, Ontario, and Fremont are based.

Figure II.1.15.5 (Source: UCR): Data collection and calibration by UCR using data from Long Beach, California

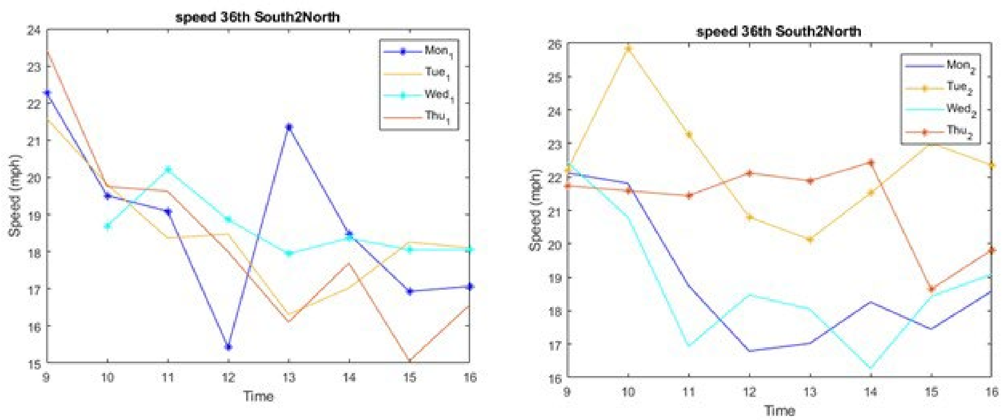

Figure II.1.15.6 (Source: UCR): Preliminary analysis over two sample weeks of data collected in Long Beach, California, shows material improvement in average speed (MPH) for the most congested approach on Atlantic Avenue. Speed, per UCR's MOVES model is one of the strongest drivers for PM2.5 emissions. Note that the trend lines with stars represent data from days when the project team's traffic signal control is activated.

Task 2.3 – Data Collection from Simulation Studies on C-ITS (with Traffic Signal Timing and Vehicle Control Co-Optimized):

Subtask 2.3.1 – The project team has been exploring the best ways to collect ATCS data with full activation of traffic signal timing optimized/prioritized and vehicle control co-optimized. Given the challenges associated with building new infrastructure/hardware/software for existing Daimler/Mercedes-Benz R&D and DHE fleets vehicles to receive SPaT, the team has been focused on provisioning that data through the beacon app. Additional data will be collected once the ability to provide SPaT data through the app has been completed.

Figure II.1.15.7 (Source: DHE): One of the integrated DHE heavy-duty trucks that are sharing movement data

Subtask 2.3.2 – The project team has been exploring the best ways to collect CAV data with full activation of traffic signal timing optimized/prioritized and vehicle control co-optimized. Given the challenges associated with building new infrastructure / hardware / software for existing Daimler/Mercedes-Benz R&D and DHE fleets vehicles to receive SPaT, the team has been focused on provisioning that data through the beacon app. Additional data will be collected once the ability to provide SPaT data through the app has been completed.

In combination, the project team has already achieved the Budget Period 2 go/no-go milestone of starting to deliver CV trajectory data set that meets NREL/UCR modeling requirements for MEP/F-MEP and Environmental Impact Analysis.

Conclusions

The project team has been able to continue making steady progress towards project goals in the past 12 months. A real-world, in-street ATCS system to research and develop Xtelligent PF ATCS within the freight context is operating consistently, and months of data from deployment sites have been collected for analysis. There have been some unforeseen challenges due to legacy infrastructure that turned out to be incompatible with the project team's planned approach, so additional engineering efforts continue to be expanded to create alternate deployment and integration solutions. Due to such unforeseen costs, the project team has been focusing its resources on Long Beach and Fremont project sites. After integration, connected vehicle data from Mercedes-Benz/Daimler R&D fleet and DHE freight fleet were found to be either too sparse (since only 30-100 vehicles are operating throughout the region at any given day and these vehicles may not be traversing through the project site frequently enough) or too latent. The project team has been addressing the sample size challenge by securing access to Mercedes-Benz/Daimler production vehicles starting late 2023/early 2024. The project team has also pivoted to utilizing a smart-phone-based beacon app leveraging Ford's SmartDeviceLink for DHE's heavy-duty freight fleets, also providing more control for testing and data collection purposes. The integration of CV data with the control algorithm requires additional work to make it work seamlessly. Despite the various unforeseen challenges and on-going engineering refinement work to be completed, the data analysis already indicates 11.1% flush-time improvement for the most congested phase on Atlantic Avenue in Long Beach. This is a precursor metric that bodes well for the project team achieving its freight travel time reduction, broader mobility system travel time reduction, and road network capacity gain goals. UCR analysis is also pointing to material improvement in average speed, which is a strong driver for PM 2.5 emissions, when even just a few intersections are activated and even without the benefit of connected vehicle data.

In total, the project team continues to make steady progress and has made appropriate pivots to mitigate navigate around the unforeseen challenges it has faced. The project team has already achieved the Budget Period 2 go/no-go milestone of starting to deliver CV trajectory data set that meets NREL/UCR modeling requirements for MEP/F-MEP and Environmental Impact Analysis. We will be working closely with UCR and NREL in the coming months to continue refining the data pipeline, refine the signal control algorithm, improve the efficacy of connected vehicle in informing signal control, all towards maximizing the chances of successful C-ITS implementation and modeling efforts outlined for Budget Period 3.

Acknowledgements

We want to acknowledge our city partners since without their support and willingness to enable testing this project would not be viable. Long Beach and Fremont deserve special recognition for spearheading the deployments (Figure II.1.15.8). We also want to acknowledge our automotive OEM partners for their willingness to provide technical help and access to vehicle data, which is another important component of our project. Daimler deserves special credit for pioneering the way on the industry side and providing access to dozens of their R&D vehicles. Our research collaborator, UCR, has been a great thought partner in figuring out creative ways to prepare for impact assessment, and we look forward to working closely with NREL as the project continues to ramp up. Finally, we acknowledge the critical role that the DOE plays in making this technically risky project possible in the first place.

Figure II.1.15.8 (Source: Xtelligent): Field visit with one of the City of Fremont traffic engineering staff members in April 2023.

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