U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Energy Efficient Mobility Systems

2021 Annual Progress Report

Vehicle Technologies Office

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Disclaimer

Acknowledgements

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Additionally, we would like to acknowledge all the researchers, participants, and stakeholders that contributed to and collaborated with the Energy Efficient Mobility Systems Program this past year. The global COVID-19 pandemic which began in 2020 has continued to impact the lives of Americans—ourselves, as well as our friends, families, and colleagues—in immeasurable ways during 2021. Many sectors of our nation's transportation system rebounded from the disruption caused by the pandemic, though others—especially public transportation—have continued to struggle. EEMS researchers are applying their capabilities to pandemic-related mobility challenges while continuing to focus on the long-term opportunity for an accessible, equitable, decarbonized transportation system. We acknowledge the creativity, resilience, and perseverance of those in the EEMS community who found new ways to accomplish the program's goals.

Acronyms

A

AADT	Average Annual Daily Traffic
AC	Alternating Current
ACC	Adaptive Cruise Control
accel	Acceleration
ACS	American community survey
ACS	Advanced Combustion Systems
AER	All-electric range
AFI	Advanced Fueling Infrastructure
AFV	Alternative Fuel Vehicle
AMD	Automated Mobility District
AMT	Automated Mechanical Transmission
ANL	Argonne National Laboratory
ANN	Artificial Neural Network
AOI	Areas of Interest
APEC	Asia Pacific Economic Council
APRF	Advanced Powertrain Research Facility
APT	Pressure Sensor
ASD	Aftermarket Safety Device
AT	Autonomous Taxi
ATDM	Active Transportation Demand Management
ATW	Active Transmission Warm up
AVTE	Advanced Vehicle Testing and Evaluation

B

BaSce	Baseline and Scenario
Batt	Battery
BEAM	Framework for Behavior, Energy, Autonomy, and Mobility
BEB	Battery Next-Generation Electric Transit Bus
BET	Battery Electric Truck
BEV	Battery Electric Vehicle
BMW	Bayerische Motoren Werke AG
BSFC	Brake Specific Fuel Consumption
BSM	Basic Safety Message
BTE	Brake Thermal Efficiency

C

CAC	Charge Air Cooler
CACC	Cooperative Adaptive Cruise Control
CAE	Computer-Aided Engineering
CAEV	Connected and automated electric vehicles
CAFE	Corporate Average Fuel Economy

CAN	Controller Area Network
CAV	Connected and automated vehicles
CARB	California Air Resources Board
CCS	Combined Charging System
CW, CCW	Clockwise, Counterclockwise
CD	Charge-Depleting
CERV	Conference on Electric Roads and Vehicles
CFD	Computational Fluid Dynamics
CFDC	Commercial Fleet Data Center
CFL	Combined Fluid Loop
CH4	Methane
CHTS	California Household Travel Survey
CRHTI	Chicago Regional Household Travel Inventory
CIP	Common Integration Platform
CMAP	Chicago Metropolitan Agency for Planning
Cm3	Cubic
CNG	Compressed Natural Gas
CO	Carbon monoxide
CO_2	Carbon Dioxide
COMM	Commuter
Conv	Conventional Vehicle
COP	Coefficient of Performance
CPT	Cumulative prospect theory
CRADA	Cooperative Research and Development Agreement
CS	Charge Sustaining
CTPP	Census transportation planning product
Cs	Cold start
CV	Conventional vehicle

D

D3	Downloadable Dynamometer Database
DC	Direct current
DCFC	Direct Current Fast Charge
DCT	Dual-clutch transmission
decel	Deceleration
DER	Distributed energy resource
DFGM	Digital Flux Gate Magnetometer
DFMEA	Design of Failure Modes Analysis
DOE	U.S. Department of Energy
DOHC	Dual overhead cam
DS	Down speeding
DSM	Distributed Security Module
DSM	Diagnostic Security Module
DSP	Digital Signal Processor
DSRC	Dedicated Short Range Communications

DTA	Dynamic traffic assignment
DWPT	Dynamic Wireless Power Transfer
dt	Change in time
dv	Change in velocity
Dyno	Dynamometer

E

EAD	Signal eco-approach and departure
EAVS	Electrically Assisted Variable Speed Supercharger
EDV	Electric Drive Vehicle
EDX	Energy dispersive x-ray spectroscopy
EERE	Energy Efficiency and Renewable Energy
EGR	Exhaust Gas Recirculation
EG/W	Ethylene glycol/water
EIA	Energy Information Agency
EOL	End of life
EPA	Environmental Protection Agency
ePATHS	Electrical PCM Assisted Thermal Heating System
EREV	Extended-Range Electric Vehicles
ESIF	Energy Systems Integration Facility
ESS	Energy Storage System
ETT	Electric Transportation Technologies
E-TREE	Electric Truck with Range Extending Engine
EUMD	End-Use Measurement Device
EV	Electric Vehicle
EVI-Pro	Electric Vehicle Infrastructure Projection Tool
EV2G	Electric Vehicle-to-Grid
eVMT	Electric Vehicle Miles Traveled
EVSE	Electric Vehicle Service Equipment
EXV	Electronic Expansion Valve

F

FAF	Freight Analysis Framework
FASTSim	Future Automotive Systems Technology Simulator
FC	Fuel cell
FC	Fast charge
FCons	Fuel consumption
FCTO	Fuel Cell Technologies Office
FCV	Fuel Cell Vehicle
FCR	Fuel consumption rate
FE	Fuel Economy
FEA	Finite Element Analysis
FEX	Front-end Heat Exchanger
FFLEET	Freight Fleet Level Energy Estimation Tool
FG	Fixed gear ratio

FGLD	Fine-grained location data
FHWA	Federal Highway Administration
FM	Friction Modifier
FMEP	Friction Mean Effective Pressure
FOA	Funding Opportunity Announcement
FTIR	Fourier transform infrared spectroscopy
FTP	Federal Test Procedure
FWD	Four-wheel drive
FY	Fiscal year

G

G	gram
GB	Gigabyte
GCEDV	Grid Connected Electrical Drive Vehicles
GEM	Gas Emissions Model
GGE	Gasoline gallon equivalent
GHG	Greenhouse Gas
GIS	Geographic information system
GITT	Grid Interaction Tech Team
GM	General Motors
GMLC	Grid Modernization Lab Consortium
GnPs	Graphene nanoplatelets
GO	Graphene Oxide
GPS	Global Positioning System
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Transportation
GSF1	Generic Speed Form 1
GSU	Grid side unit
GUI	Graphic User Interface
GVW	Gross Vehicle Weight

H

HC	Unburned hydrocarbons
HD	Heavy Duty
HEV	Hybrid-Electric Vehicle
HHDDT	Heavy Heavy-Duty Diesel Truck
HHV	Hydraulic Hybrid Vehicle
HIL	Hardware-In-the-Loop
HP	Heat Pump
Hp	Horsepower
HTML	HyperText Markup Language
HV	High Voltage
HVAC	Heating Ventilating and Air Conditioning
HWFET	Highway Fuel Economy Test
HPMS	Highway Performance Monitoring System
HVTB	High Voltage Traction Battery

HWY	Highway Program or Highway Fuel Economy Test Cycle
HPC	High-Performance Computing
HTR	Heater
Hz	Hertz

I

I	Inertia
IC	Internal Combustion
ICDV	Internal Combustion Drive Vehicles
ICE	Internal Combustion Engine
ICTF	Intermodal Container Transfer Facility
ICU	Inverter-Charger Unit
IEB	Information Exchange Bus
IEC	International Electrotechnical Commission
IGBT	Insulated Gate Bipolar Transistors
INL	Idaho National Laboratory
IOT	Internet of Things
IR	Infrared Radiation
ISO	International Organization for Standardization
ITS	Intelligent Transportation Systems

J

JIT	Just-in-Time

K

kg	Kilogram
km	Kilometer
kW	Kilowatt
kWh	Kilowatt hour

L

L	litre
L1	Level 1 benchmark
L2	Level 2 benchmark
Lbf	Pounds force
LCC	Liquid-Cooled Condenser
LCV	Long combination vehicle
LD	Light duty
LH	line haul
Li	Lithium
LIB	Lithium-ion battery
LLNL	Lawrence Livermore National Laboratory
LV	Leading Vehicle

M

M	Mass
MaaS	Mobility as a Service
MBSE	Model Based System Engineering
MEP	Mobility energy productivity (MEP)
MD	Medium Duty
mpg	Miles per gallon
MMTCE	Million Metric Tons of Carbon Equivalent
MIIT	Ministry of Industry and Information Technology
mi	Mile
MJ	Megajoules
MONLP	Multi-Objective Non-Linear Program
MOSFET	Metal-Oxide Semiconductor Field-Effect Transistor
MNL	Multinomial Logit
mph	Miles per hour
MPGe	Miles per gallon equivalent, Miles per gallon gasoline equivalent
MTC	Metropolitan Transportation Commission
MTDC	Medium Truck Duty Cycle
MOVES	Motor Vehicle Emission Simulator
MPR	Market Penetration Rates
MRF	Moving Reference Frame
MY	Model year
M2	Meters squared

N

NACFE	North American Council for Freight Efficiency
NCCP	Normalized cross-correlation power
NDA	Non-Disclosure Agreement
NETL	National Energy Technology Laboratory
NHTS	National Household Travel Survey
NHTSA	National Highway Transportation Safety Administration
NM	Newton meters
NOx	Nitrogen oxides
NR	Natural Rubber
NRE	Non-Recurring Engineering
NREL	National Renewable Energy Laboratory
NRT	National Retail Trucking
NVH	Noise, vibration, and harshness

O

OBC	On-board charger
OCBC	Orange County Bus Cycle
OEM	Original Equipment Manufacturer
ORNL	Oak Ridge National Laboratories

P

P	Active Power
PC	Polycarbonate
PCM	Phase-Change Material
PCU	Power Control Unit
PCU	Powertrain Control Unit
PEV	Plug-In Electric Vehicle
PFC	Power factor correction
PFI	Port fuel injection
PHEV	Plug-in Hybrid Electric Vehicle
PHEV##	Plug-in hybrid electric vehicle with ## miles of all-electric range
PI	Principal Investigator
PID	Proportional+Integral+Derivative
PM	Permanent Magnet
PM	Particulate Matter
PMT	Passenger/Person Miles Traveled
ppm	Parts per Million
PTC	Positive Temperature Coefficient (Electric Heater)
PTO	Power Take-Off
PVP	Polyvinylpyrrolidone
λ	Power Factor
φ	Power Angle

Q

Q	Reactive power
QA	Quality assurance
QC	Quality control

R

R2	Coefficient of Determination
R/D	Receiver / Dryer
REx	Range Extending Engine
rGO	reduced graphene oxide
RH	Relative Humidity
RMS	Root Mean Square
ROL	Ring-On-Liner
rpm	Revolutions Per Minute
RSU	Roadside Unit
RWDC	Real-World Drive-Cycle

S

S	Apparent power
SAE	Society of Automotive Engineers
SAV	Shared Automated Vehicles

SDO	Standards Definition Organizations
SI	Système International d'Unités
SI	Gasoline Spark Ignition
SMART	Systems and Modeling for Accelerated Research in Transportation
SNR	Sensor
SOC	State of Charge
SPaT	Signal phase and timing
SPL	Sound Pressure Level
SR	Speed Ratio
SS	Steady State
S/S	Start/Stop
SPaT	Signal Phase and Timing
SVET	Smart vehicle energy technology
SVTrip	Stochastic Vehicle Trip Creator

T

T	Torque
TA	Technical Area
TA	Torque Assist
TC	Thermocouple
TAZ	Traffic Analysis Zone
TCO	Total cost of ownership
TE	Thermoelectric
TE	Transmission Error
TES	Thermal Energy Storage
TGA	Thermogravimetric analysis
THC	Total hydrocarbon emissions
TIM	Thermal Interface Materials
TLRP	Thermal Load Reduction Package
TN	Testing Network
TNC	Transportation Network Companies
TOU	Time-Of-Use
TRB	Transportation Research Board
TTC	Time to Collision
TV	Trailing Vehicle
TXVs	Thermal Expansion Valves

U

U.S. DRIVE	U.S. Driving Research and Innovation for Vehicle Efficiency and Energy Sustainability
UC	Ultra-capacitor
UCR	University of California, Riverside
UDDS	Urban Dynamometer Driving Schedule
UM	University of Michigan
UPS	United Parcel Service
URL	Uniform Resource Locator

Util	Battery capacity utilization

V

V	Voltage
V2I	Vehicle-to-Infrastructure
V2V	Vehicle to Vehicle
VAr	Volt-Amp-reactive
VHT	Vehicle hours traveled
VIP	Vacuum insulated panels
VKT	Vehicle kilometers traveled
VMT	Vehicle miles traveled
VOTT	Value-of-travel-time
VPPG	Virtual-Physical Proving Ground
VSI	Vehicle Systems Integration
VTO	Vehicle Technologies Office

W

Dw	Change in Angle W
WCC	Water Cooled Condenser
Wh	Watt hour
WHR	Waste Heat Recovery
WPT	Wireless Power Transfer
WTP	Willingness to pay
WTW	Well-to-Wheels

X

XPS	X-ray photoelectron spectroscopy

Y

Z

ZOV	Zero-occupancy 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 and ride-hailing 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 global 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. In 2021, the transportation sector largely rebounded from the initial impacts of the pandemic-related disruptions; however, other modes such as public transit and shared mobility continue to struggle. 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 mobility energy productivity (MEP), or the energy efficiency, affordability, and access provided by the transportation system. Increases in MEP result from improvements in the quality or output of the transportation system and/or reductions in the energy and cost of transportation.

EEMS Program activities during FY 2021 focused on analytical research 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 R&D projects are summarized within (4) the Connectivity and Automation Technology key activity area. Each of the individual progress reports provide a project overview and highlights of the technical results.

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Vehicle Technologies Office Overview

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

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

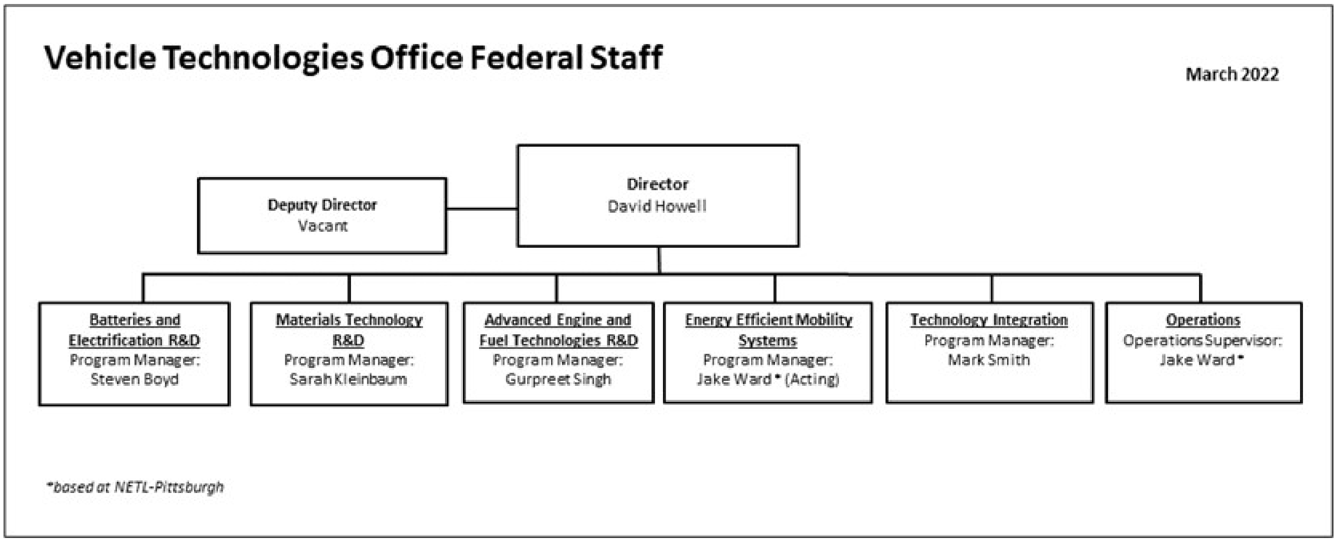
VTO is uniquely positioned to accelerate sustainable transportation technologies due to strategic public-private research partnerships with industry (e.g., U.S. DRIVE, 21st Century Truck Partnership) that leverage relevant expertise. These partnerships prevent duplication of effort, focus DOE research on critical RDD&D barriers, and accelerate progress. VTO advances technologies that assure affordable, reliable mobility solutions for people and goods across all economic and social groups; enable and support competitiveness for industry and the economy/workforce; and address local air quality and use of water, land, and domestic resources.

Annual Progress Report

As shown in the organization chart (below), VTO is organized by technology area: Batteries & Electrification R&D, Materials Technology R&D, Advanced Engine & Fuel Technologies R&D, Energy Efficient Mobility Systems, and Technology Integration. Each year, VTO's technology areas prepare an Annual Progress Report (APR) that details progress and accomplishments during the fiscal year. VTO is pleased to submit this APR for Fiscal Year (FY) 2021. The APR presents descriptions of each active project in FY 2021, including funding, objectives, approach, results, and conclusions.

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

Organization Chart



Energy Efficient Mobility Systems Program Overview

Introduction

On behalf of the Energy Efficient Mobility Systems (EEMS) Program of the U.S. Department of Energy's (DOE's) Office of Energy Efficiency and Renewable Energy (EERE) Vehicle Technologies Office (VTO), we are pleased to submit this Annual Progress Report (APR) for Fiscal Year (FY) 2021.

The introduction of disruptive transportation technologies and services, such as connected and automated vehicles, car-sharing, and ride-hailing 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 global 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; however, modes such as public transit and shared mobility continue to struggle. 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 2021 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 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. Mobility energy productivity (MEP) is used as a 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 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 of future integrated mobility systems.

STRATEGIC GOAL #2: Identify and support early-stage R&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:

- Systems & Modeling for Accelerated Research in Transportation (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 FY2021, the EEMS Program launched "SMART Mobility 2.0", building upon the research results and insights from the first phase of SMART Mobility. This new phase includes 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 includes 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.

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 multilab 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 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 R&D focuses on innovative, early-stage, 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 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 R&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 FY2021 Program-Wide Funding Opportunity Announcement entitled, "Implementation of Energy Efficient Mobility Systems Technologies into Real-World System Applications."

Coordination between EEMS and other federal programs focused on connected, automated, and efficient transportation systems is critically important. EEMS participates in planning discussions with various modal administrations within USDOT, including the Federal Highway Administration (FHWA), Federal Transit Administration (FTA), and the Intelligent Transportation Systems Joint Program Office (ITS-JPO). Coordination with USDOT is important due to the linkage between VTO's R&D activities to create efficient, secure, and sustainable transportation technologies, and USDOT's mission to ensure our nation has the safest and most efficient and modern transportation system in the world.[5]

In addition to intergovernmental collaboration with the USDOT, 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.[6] 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)[7], by pursuing collaborative R&D to

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

realize its vision for our nation's trucks and buses to safely and cost-effectively move larger volumes of freight and greater numbers of passengers while emitting little or no pollution. The EEMS Program is directly involved with the Freight Operational Efficiency Technical Team within the truck partnership.

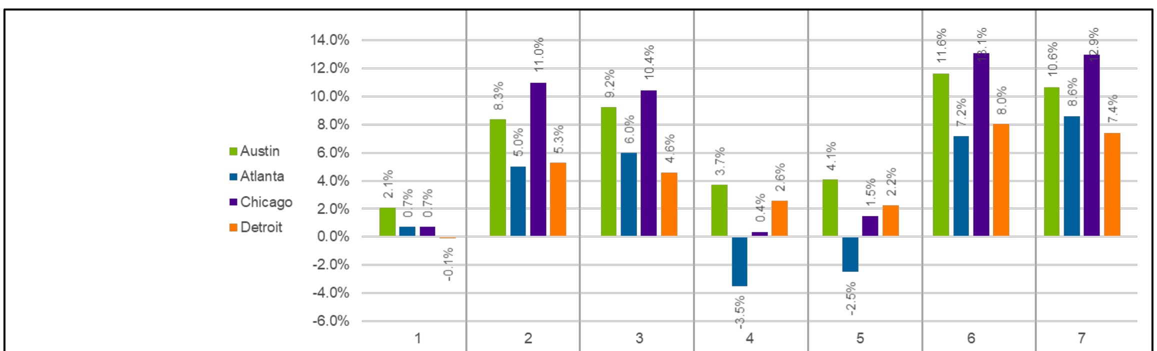
The EEMS Program continually seeks additional high-value opportunities to engage with relevant stakeholders in order to share EEMS-funded research results and learn from other mobility-related efforts. For example, the EEMS Program is a governmental sponsor and member of the National Academies/Transportation Research Board Forum on Preparing for Automated Vehicles and Shared Mobility[8], 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. 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 provides input and review to the research conducted by the Consortium and helps ensure the work performed is aligned with a variety of mobility stakeholders. As the Consortium focuses on completing and deploying its integrated modeling workflow during SMART Mobility 2.0, it will continue to pursue collaborations and partnerships with local city governments, transportation planning organizations, and other stakeholders to inform transportation policy making.

Project Funding

VTO selects and funds critical research through a combination of competitive funding opportunity announcement (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

- As part of SMART Mobility 2.0, ANL researchers used the SMART Mobility Integrated Modeling Platform comprised of POLARIS, SVTrip, Autonomie, UrbanSim, and MEP to quantify the impact of individual modes, technologies, and managements strategies, and how they collectively affect the



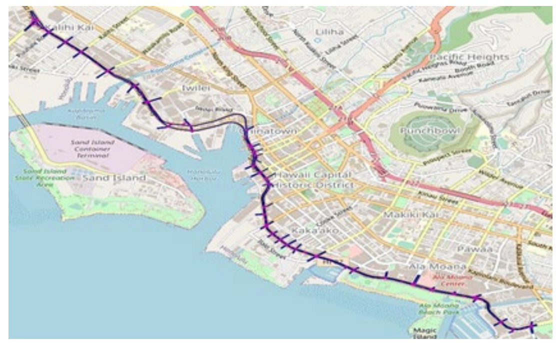
Scenario ID	0	1	2	3	4	5	6	7
RSU/CV%	0	0	0	0	0	0	0	0
CACC/VOT	Base	Base	Base	Base	75% / HIGH	75% / HIGH	75% / HIGH	75% / HIGH
ROAD PRICE	Base	Base	Delay-based	Delay-based	Base	Base	Delay-based	Delay-based
OFF-HOURS	0	5% shift	0	5% shift	0	5% shift	0	5% shift

Change in Network Speed Under Different Scenarios of Technology Deployment

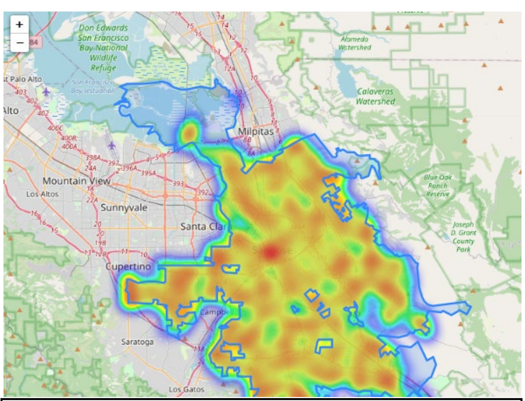
8 https://www.nationalacademies.org/our-work/forum-on-preparing-for-automated-vehicles-and-shared-mobility-services

transportation system as a whole. A traffic flow study of different road pricing strategies concluded that delay-based road pricing outperformed all other strategies, leading to a 10% reduction of vehicle hours traveled (VHT) and energy consumption. A study of roadside connectivity illustrated that even moderate penetration rates of roadside units with 25% penetration of connected vehicles can recover about 50% of the delay induced by random incidents. A study of off-hours freight delivery showed that shifting 5%-6% of deliveries to overnight hours could benefit both delivery fleets and the overall transportation system, with a 2.3% increase in heavy duty truck speed and a 7%-8% increase in medium duty speeds. Lastly, behavioral studies for cooperative adaptive cruise control (CACC) demonstrated work trips are as long in 2035 under the CACC scenario as they are in the base year, while without CACC, work trips would be 15% shorter on average. *(I.1.9 – SMART Mobility Laboratory Consortium 2.0: Studies, Argonne National Laboratory)*

- A research team from Oak Ridge National Laboratory (ORNL), the University of Hawaii (UH), and Econolite Systems is working to achieve energy savings and reduction in travel delay by incorporating artificial intelligence (AI)-based modeling and control, networked intersectional modeling, and signal infrastructure hardware and controls for the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu, Hawaii. Modeling results from this new project illustrate an average modeling error of <10%, demonstrating that the new hybrid neural network (HNN) modeling approach can be readily used for AI-based control system design. A technical publication on this work received the best paper award from the 2021 Vehicular Conference in France[9]. Next steps include establishing a VISSIM simulation testing system to accommodate the control algorithm design. *(I.2.4 – Applying Artificial Intelligence (AI) Based Signal Coordination and Controls for Optimized Mobility for the Nimitz Highway and Ala Moana Boulevard Arterial in Honolulu)*



Nimitz Highway / Ala Moana Boulevard Corridor



A heat map of work trip destinations in the city of San Jose taken from Mobiliti's [interactive web report.]

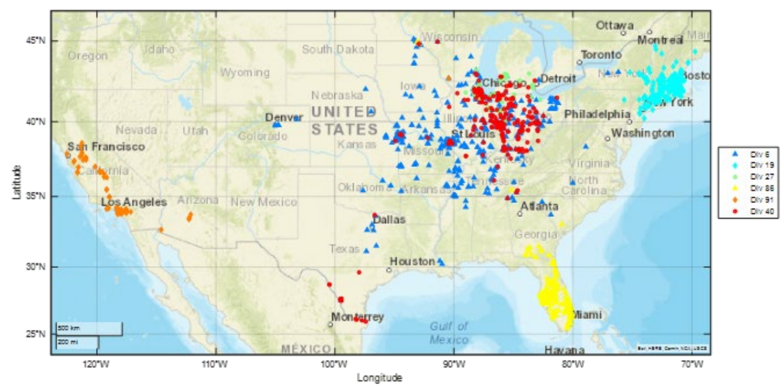
- Lawrence Berkeley National Laboratory (LBNL) has developed Mobiliti, an integrated data analytics platform driven by high-performance computing (HPC) that can be used for solving transportation problems at scale. The team has used artificial intelligence (AI) to build models that can be transferred to organizations that do not have access to HPC resources. In FY2021, the team worked closely with the city of San Jose to develop a cities factsheet, a sharable and interactive web report that can showcase Mobiliti's applications. A long-term vision for the Mobiliti platform is to use it as a digital twin for a region. (I.2.1 – Big Data System for Mobility Phase 2)

[9] Hybrid Neural Network Modeling for Multiple Intersections along Signalized Arterials - Current Situation and Some New Results (energy.gov)

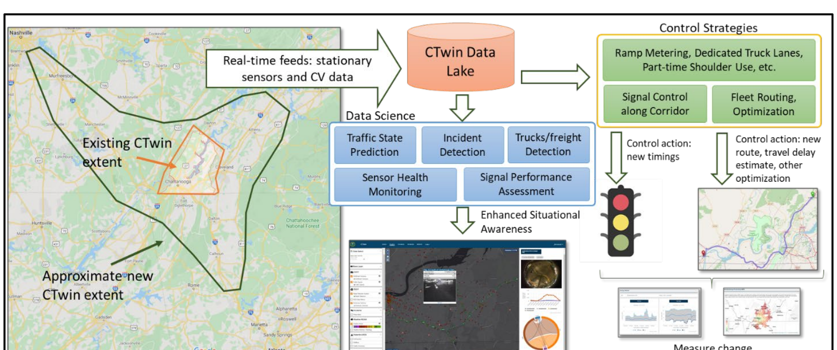
Using a driving simulator to evaluate a network's ability to perceive objects under various lighting conditions. Source: ORNL

- Development of an artificial intelligence (AI) software has been licensed by General Motors (GM) to help accelerate the development of advanced driver assistance technologies. Oak Ridge National Laboratory (ORNL) developed Multinode Evolutionary Neural Networks for Deep Learning (MENNDL), a software that can quickly answer questions such as how can cars quickly and accurately perceive their surroundings to navigate safely around them, which is one of the biggest obstacles facing the adoption of driver assistance technology. MENNDL provides GM the ability to design thousands of neural networks in hours versus months or years and determine which is the most promising. Leveraging advanced neural networks that can instantly analyze on-board camera feeds and correctly label each item in the vehicle's field of view has the potential to enable more energy efficient use for cars, while simultaneously increasing their onboard computing capacity. *(I.2.5 – High-Performance Computing (HPC)-Enabled Artificial Intelligence for Connected and Automated Vehicle Development)*

- Cummins, along with partners UC-Berkeley, Argonne National Laboratory (ANL), and Venture Logistics, is developing, implementing, and validating a learning-based automated and optimal freight management system that is used to demonstrate freight operation system efficiency improvements of 20% or more over a baseline fleet system that covers multiple transportation modes, including long-haul, short-haul and less-than-truckload (LTL), and/or pick-up and delivery (P&D). The team has successfully developed a novel artificial intelligence (AI) and first principle freight system simulation model that has been validated with actual fleet data and is positioned to implement solutions that integrate advanced powertrains and connected and automated technologies into the freight operation system. *(II.1.9 – Connected and Learning Based Optimal Freight Management for Efficiency)*



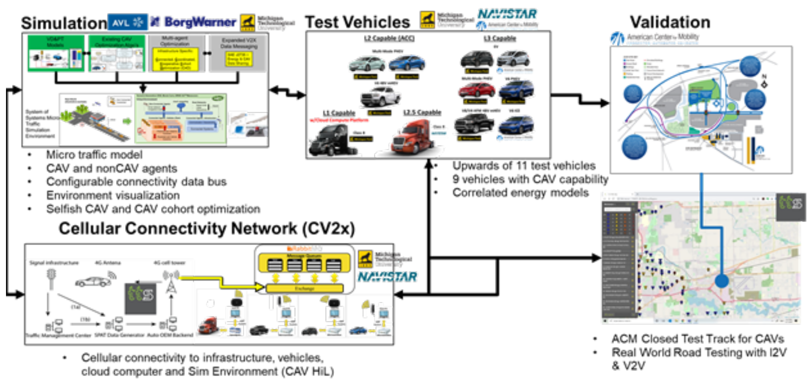
Venture fleet operation locations for selected divisions. Divisions are a mix or regional and over the road (OTR) operations that cover most of the U.S.



Illustrative Schematic for Inter-Regional CTwin Model

- Oak Ridge National Laboratory (ORNL) and the National Renewable Energy Laboratory (NREL) have developed CTwin, a regional-scale, open, scalable, real-time situational awareness platform that brings in 500+ primary data streams from seven proprietary vendor systems across three institutions, in addition to over forty distinct data layers, to create a unique capability: *a real-time digital twin of the transportation system of Chattanooga, TN.* The goal of the current research is to employ artificial intelligence (AI) and high-performance computing (HPC) methods to geographically and computationally scale up the Chattanooga Digital Twin, CTwin, to achieve over 20% energy savings across city streets and freeways for passenger traffic, freight, and connected vehicles (CVs). The project has begun to implement these solutions in a real world setting and demonstrated proof of concept that a digital twin can be developed, and then used to develop implementable solutions for cities to improve traffic, reduce congestion, and improve vehicle operational efficiency. *(I.2.2 – Scaling up the Real-Time Data, Simulation & Artificial Intelligence (AI), and Control for Optimizing Regional Mobility in the United States)*

- A project team led by Michigan Technological University (MTU) with partner organizations AVL Powertrain Engineering Inc. (AVL), Borg Warner (BW), Traffic Technology Services (TTS), American Center for Mobility (ACM), and Navistar (NAV) developed the capability to model and optimize cohort behavior for energy optimization on single-lane and multi-lane roadways with multi-signalized intersections. For one of the scenarios, a trained artificial intelligence (AI) coupled with a classifier to determine pass/fail criteria (e.g., the ability to maintain cohort integrity and the ability to pass signalized intersections) allowed the cohort to smoothly navigate the traffic maze without having to stop at a single traffic light, resulting in energy savings of 17% with the AI alone, and an additional 10% savings when the AI is combined with the classifier output. Next steps include completing a third infrastructure optimization method for limited access highway and integration into the simulation environment, and maturation of the cellular connectivity network (CV2x) that links the simulation environment as a cloud based connected and automated vehicle (CAV) hardware in the loop (HiL) and cohort optimization tool. *(II.1.2 – Energy Optimization of Light and Heavy-Duty Vehicle Cohorts of Mixed Connectivity, Automation and Propulsion System Capabilities via Meshed Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) and Expanded Data)*



Summary of combined math to track the approach for CAV cloud based cohort optimization for energy reduction

We are pleased to submit the Annual Progress Report for the Energy Efficient Mobility Systems Program for FY 2021. Inquiries regarding the EEMS Program and its research activities may be directed to the undersigned.

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I Computational Modeling and Simulation

This chapter describes FY2021 research results from the Computational Modeling and Simulation key activity of the EEMS Program. This key activity focuses on the development and application of computational methods and approaches to understand the future of transportation and develop computer-based solutions that promote an improvement in mobility energy productivity. The Computation Modeling and Simulation key activity includes the following R&D portfolios: 1) SMART Mobility 2.0, 2) Artificial Intelligence, High-Performance Computing, and Data Analysis, and 3) Core Simulation and Evaluation Capabilities.

I.1 SMART Mobility 2.0

I.1.1 Development and Validation of Intelligent CAV Controls for Energy-Efficiency (Argonne National Laboratory)

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Start Date: October 1, 2020 End Date: September 30, 2021
Project Funding: $2,050,000 DOE share: $2,050,000 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 [1], and 51% had Level-1 automation (Shirokinskiy, Bernhart, and Keese 2021), promising greater convenience and safety. Vehicle-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 (Han, Karbowski, and Kim 2020) and "speed+powertrain" co-optimization (Shen et al. 2020). 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 (Karbowski et al. 2020).

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 Anything-in-the-loop

(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 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 many 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 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.

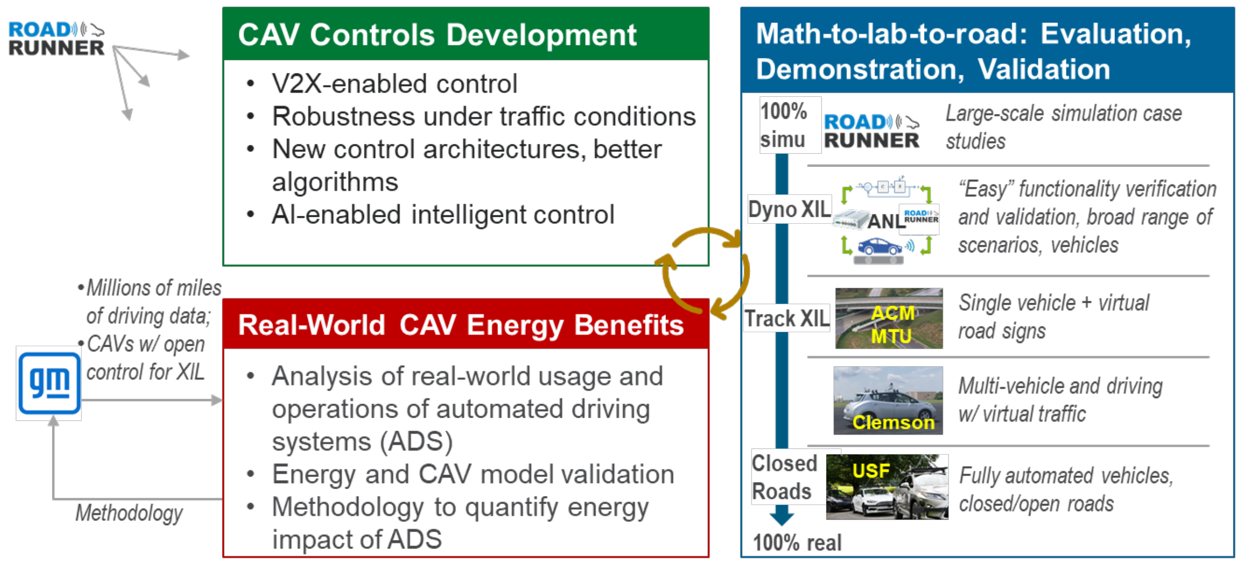

Figure I.1.1.1 Development and validation of intelligent CAV controls for energy efficiency (project approach).

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 American Center for Mobility (ACM) on vehicles prepared by Michigan Technological University (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 University of South Florida (USF) will conduct tests using L3 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 CRADA partner for this task and provides real-world driving data from fleet vehicles equipped with automated driving technology.

Results

Task 1: Intelligent vehicle control technology development

V2I-enabled eco-approach with multiple traffic lights. We improved the V2I-enabled eco-driving control to take advantage of longer V2I connectivity range and perform multi-traffic signal eco-approach (previously, the control used one traffic signal at a time). In the long-range V2I-enabled eco-driving control, the *green window selector* on the upper level finds a series of green windows for each intersection. Then, the *reference trajectory generator* on the lower level computes the reference trajectories, subject to the constraints imposed by the selected green windows. We focused on improving the long-range V2I-enabled "speed-only" eco-driving control so that it generates smooth trajectory catching feasible green light windows over multiple connected traffic lights. As shown in Figure I.1.1.2, CAVs equipped with this new version of eco-driving controls can "see" further ahead with the increased connectivity range; change their speed less frequently, resulting in smoother accelerations and no full stop at the intersections; and achieve more energy savings. In the short scenario described in Figure I.1.1.2, when the connectivity range is set to 800m, the CAV with this new control saves 15% more energy compared to a case with 250m range.

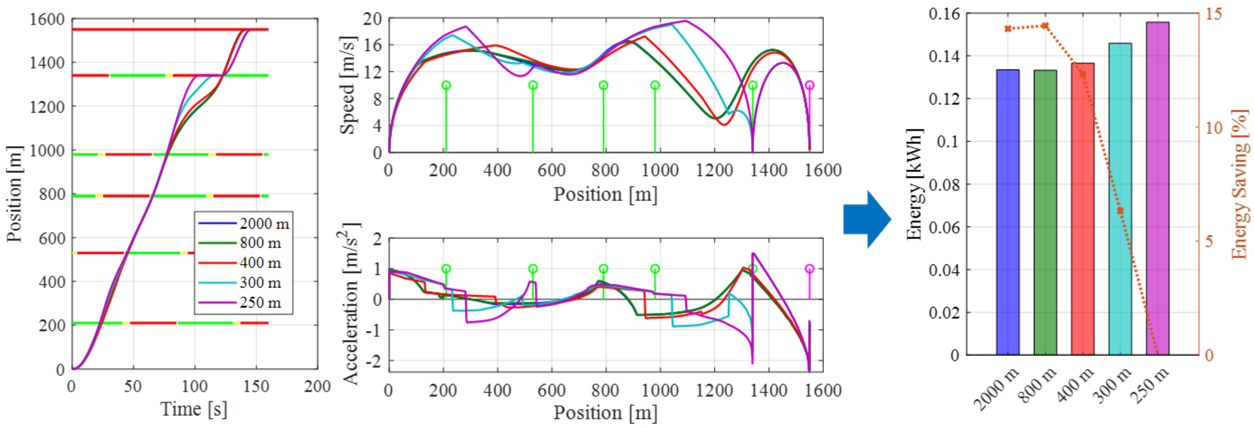

Figure I.1.1.2 RoadRunner results of the long-range V2I-enabled speed-only eco-driving control with five V2I connectivity ranges between 250 and 2000m.

V2V-enabled preceding vehicle speed prediction. We developed a real-time capable short-/mid-term prediction of the front vehicle speed, based on locally weighted polynomial regression, as shown in Figure I.1.1.3. The prediction model takes the point measurements of speed and position of preceding vehicles in the same lane as inputs, and outputs the speed profile of the immediately preceding vehicle ("target" vehicle). We then coupled the enhanced speed prediction enabled by V2V with the "speed+powertrain" eco-driving control. Energy savings increased by up to 4% when both V2V and V2I were employed, compared to sensor-based and V2I-enabled prediction (and no V2V).

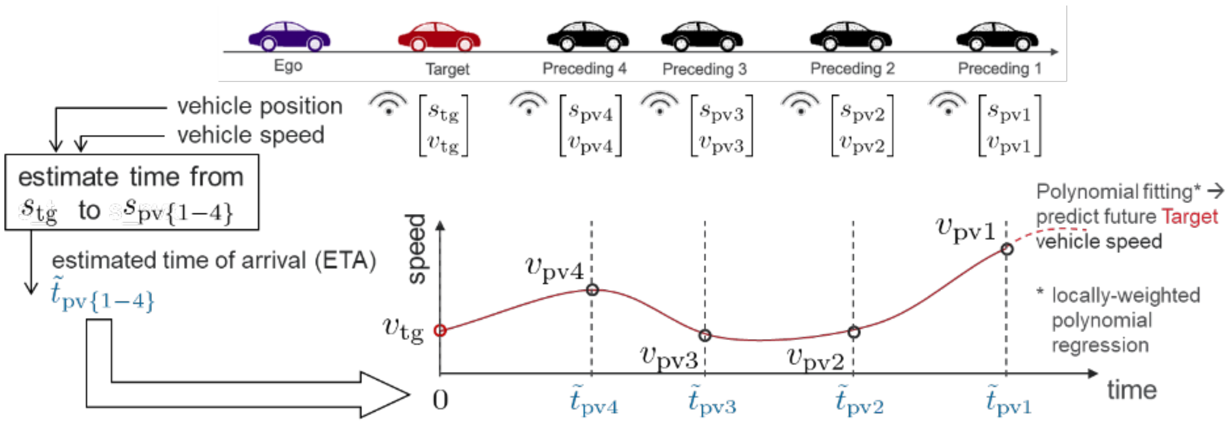

Figure I.1.1.3 V2V-enabled prediction using locally weighted polynomial regression.

Controls improved and verified under traffic conditions. We used the prototype linkage between SUMO (traffic flow simulator) and RoadRunner developed in SMART 2.0 Workflow task to identify and correct potential faults of one of our existing controls ("powertrain+speed" control) in complex traffic situations. The first improvement was made on the traffic signal eco-approach with a standing queue, as displayed in Figure I.1.1.4a. The new version of "powertrain+speed" estimates the delay time by dividing the standing queue length by a dissolving rate, effectively avoiding the unnecessary stop. The second improvement took place in handling unexpected cut-ins, as shown in Figure I.1.1.4b. The new "powertrain+speed" is forced to refresh (originally at a fixed distance-based rate of 25 m) when detecting a large error in the front vehicle prediction from the last step, which allows a recalculation incorporating the cut-in vehicle in distance constraints. In addition, the headway time is lengthened to allow yielding to the cut-in. Overall, after applying these improvements and other bug fixes such as stabilizing the target cruising speed when following a vehicle, the energy consumption on the selected route (in Chicago) was reduced by 4%, compared to the original version.

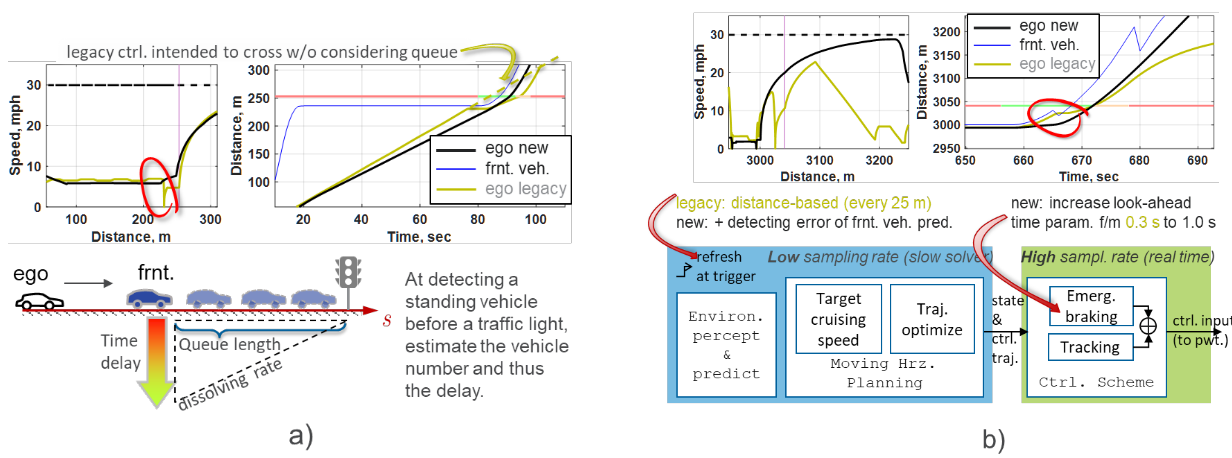

Figure I.1.1.4 Improved 'powertrain+speed' (ego legacy control) a) on eco-approaching by estimating the time delay due to the queue, b) emergency response to unexpected cut-ins.

New "powertrain-aware" eco-driving control. Nonlinearities within the eco-driving control problem exist in the complex energy conversion/dissipation in powertrain, environmental influences such as road grade and aerodynamic drag, and constraints due to traffic signs, safety issues, and physical limits of the vehicle system. They are essential to the energy-saving potential and the feasibility of the obtained solution. To take the nonlinearities into account, especially from the powertrain and road grade point of view, we created a new data-driven powertrain-aware model predictive control using Koopman linearization (*PT-aware*). It offers an intermediate option between the *speed-only* control (which is easy and universal to deploy but may be limited in its savings) and the *powertrain+speed* (which is the opposite).

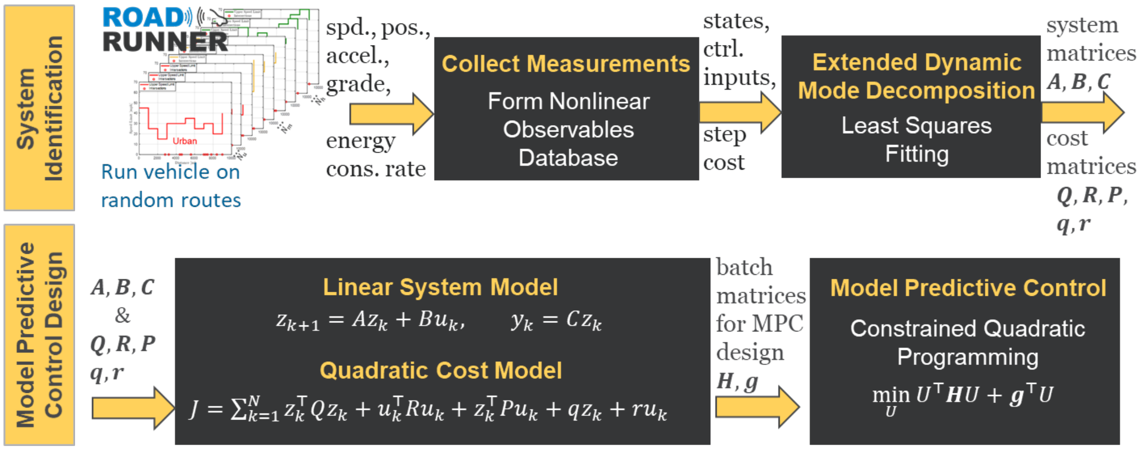

Figure I.1.1.5 Workflow of designing a data-driven powertrain-aware model predictive control (PT-aware).

The novelty of the *PT-aware* control is the data-driven framework to generate a linear-quadratic approximation for the longitudinal vehicle dynamics and the energetic cost in a higher-dimensional state space (in reference to the original state space of speed and position). Thus, we can encompass the nonlinear features (e.g., road grades and powertrain inefficiencies) in a linear-quadratic formulation with the describing matrices, as illustrated in Figure I.1.1.5, and apply model-predictive control. The *PT-aware* control was implemented in RoadRunner and the entire training and model generation process is automated, from collecting measurements data by running a selected vehicle on randomized routes, over generating the matrices for the model predictive control design, to finally building the model block integrated in RoadRunner. In the first evaluation test, *PT-aware* control offers an additional 2-3% of energy savings compared to the *speed-only* control (a representative example of linear control), when considering the trade-off for travel time: a positive result, given that the *speed-only* has been more maturated.

Prototype of real-time controller using AI. In FY21, we developed the first prototype of eco-driving controls featuring AI with Deep Reinforcement Learning (DRL). A subfield of machine learning that combines reinforcement learning (RL) and deep neural networks, DRL is a model-free algorithm that can be applied to optimal control problems, especially for highly non-linear systems. We combined DRL with the non-AI speed-only control speed optimization planner to build an AI-enabled real-time intelligent speed optimization planner for CAV control. A deep Q-learning algorithm is implemented in the training, and the agent with a Long Short-Term Memory (LSTM) neural network model learns how to estimate the optimal parameters for the speed optimization planner to save maximum energy. The DRL algorithm is built into MATLAB with an RL toolbox. In the case study, it can offer up to 12% more savings with untrained SPaT cases in simple scenarios (Figure I.1.1.6). For more advanced DRL algorithms and more efficient training, we also created a linkage between MATLAB/Simulink-based RoadRunner models and Python, thus enabling training with PyTorch and TensorFlow.

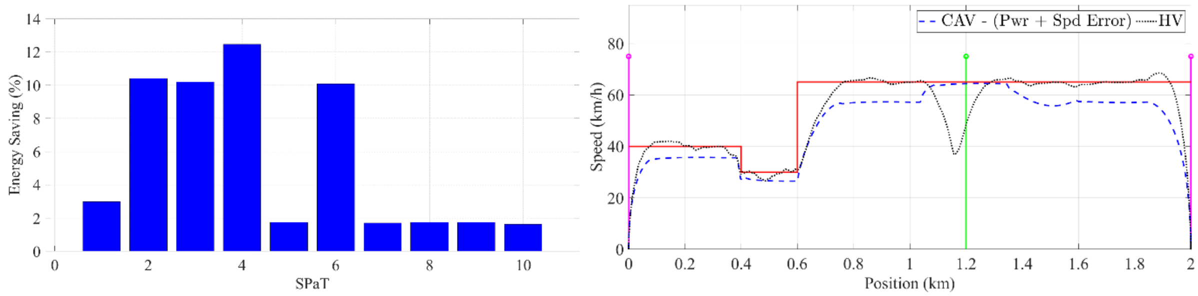

Figure I.1.1.6 Energy savings by RL-combined intelligent control in different untrained SPaT cases and speed trajectory for one case.

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

Argonne's CAV controls successfully implemented and demonstrated on dynamometer with Argonne's XIL workflow. In preparing for implementation, the "speed-only" control underwent some adaptation so that it links properly with the vehicle (e.g., pedal mapping) and thoroughly exercised it in simulation. The control was then integrated with the hardware via dSpace MicroAutoBox. We created five single-vehicle, and two multi-vehicle test routes to check the control functionality and to evaluate energy impact of the controls in various conditions on the real vehicle, resulting in a total of 28 scenarios—combinations of seven routes and five control (baseline, with or without V2I, and two different calibrations). We conducted seven testing campaigns in FY21, accumulating 17 dynamometer-days, 734 km and 207 tests scenarios for the Chevrolet Bolt and Blazer to validate the controls functionality, improve the test repeatability, and prepare for track testing (ACM and Clemson). In conducting three tests, we observed only a 1% discrepancy in terms of travel time and energy consumption.

Energy saving demonstrated for a lead vehicle using XIL workflow. We demonstrated up to 22% in energy saving without any functional failures by the eco-driving control on the Chevrolet Bolt 2017 (Figure I.1.1.7). The greatest energy saving was achieved in the scenario of route #5, which combines various speed limit changes and traffic signal conditions, when using V2I-enabled traffic signal eco-approach. The eco-driving control with V2I can save about 13% more energy than the control without V2I.

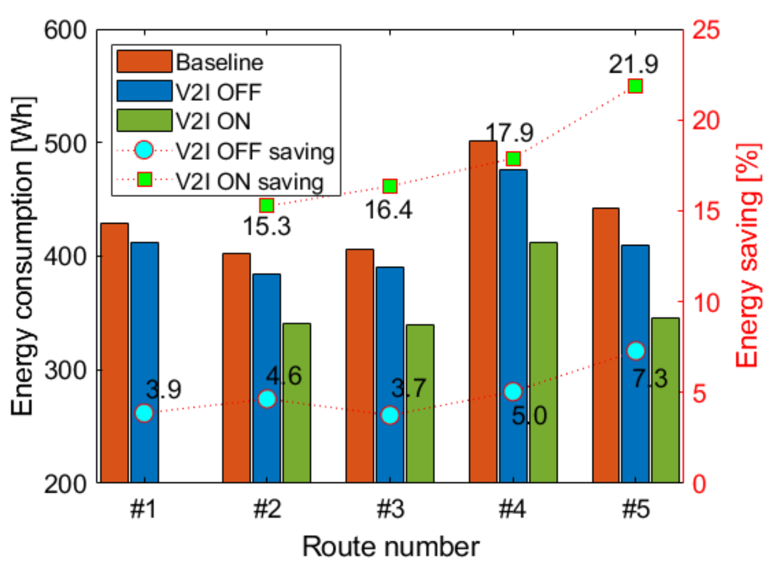

Figure I.1.1.7 Energy consumption/savings for lead on five routes.

Energy saving demonstrated for scenario with preceding vehicle (using XIL workflow). Up to 16% of additional energy savings without any functional failure of the eco-driving controls when following a vehicle (Figure I.1.1.8). The greatest energy saving was achieved when all vehicles were equipped with eco-driving controls with V2I in the more congested traffic signal conditions (route #7).

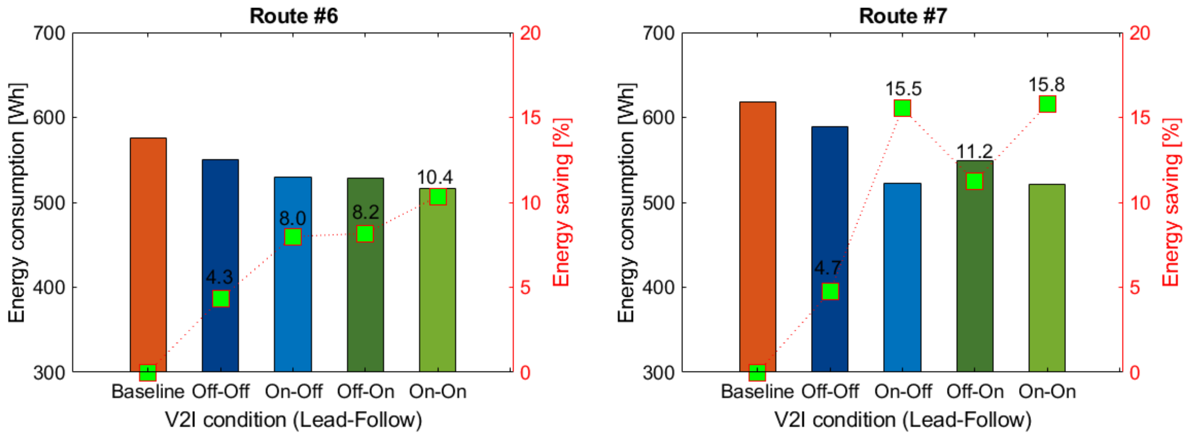

Figure I.1.1.8 Energy consumption and energy savings of up to 16% by ANL eco-driving control for a following vehicle on dynamometer in the multi vehicles scenarios with two routes.

Argonne's eco-driving control demonstrated on track at ACM. Argonne's eco-driving controls were modified and implemented in collaboration with MTU in a Chevrolet Bolt 2019 equipped with a drive-by-wire system. The five routes for single-vehicle scenarios were developed to match the length of the ACM track. From February to June 2021, ACM conducted four rounds of testing with virtual environments including speed limits, stops, and traffic signals, focusing on test procedure improvements and control functionality verification. All control functionalities worked as intended in the vehicle, which demonstrated energy savings of up to 20%. Chevrolet Bolt results will be finalized in fall 2022.

Preparation of track testing with virtual vehicles. Argonne will implement and test controls on Clemson's vehicles on a track in an XIL set-up that features virtual vehicles. In preparation for these tests, scheduled for winter 2022, we developed the integration process and tested the Argonne controls in Clemson's "Software-in-the-Loop" (SIL) setup: the Argonne controls are integrated and tested within the real-time operating system (ROS) used in the vehicle and which links with VISSIM—a traffic flow simulator that will generate the virtual vehicles. This paves the way for Vehicle-in-the-Loop testing on track. We verified in VISSIM that the Argonne V2I-enabled spd-only eco-driving controller works properly at various penetration rates (0 – 40 %), traffic volumes (450 – 950 veh/h), and V2I connectivity ranges (300 – 2,000 m) for single-lane scenarios. As shown in Figure I.1.1.9, CAVs (blue line) smoothly pass through all traffic lights without collision by reducing speed in advance using signal phase and timing (SPaT) information; human-driven vehicles (black line) benefit from following the CAV. Increasing CAV penetration rates reduced unnecessary stops for all vehicles entering the corridor and made a speed harmonization effect that can smooth traffic by reducing the stop-and-go waves.

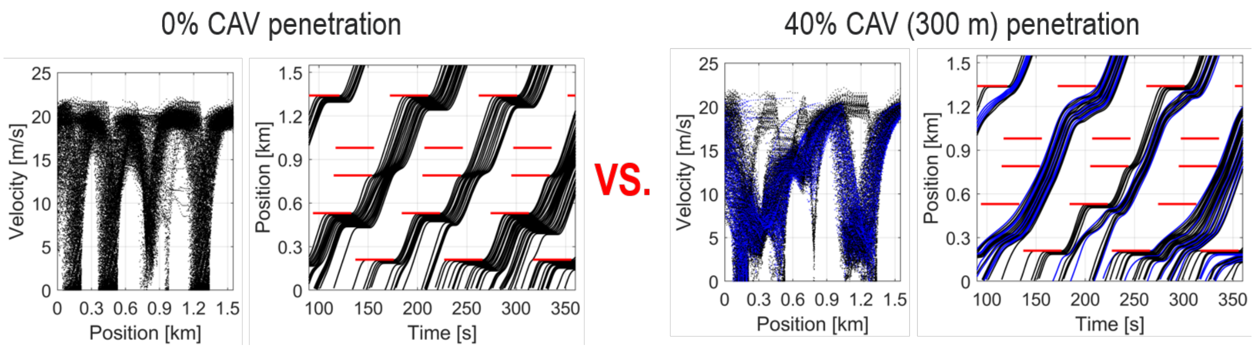

Figure I.1.1.9 ANL controller ROS SIL VISSIM testing result examples, given the traffic volume of 950 veh/h: 0 % penetration rates as a baseline case and 40 % CAV penetration rates with V2I connectivity range of 300 m

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

Through a CRADA partnership, GM provides a great amount of data from vehicles equipped with automation (SuperCruise Systems). The data come from GM-owned fleet vehicles with high-frequency loggers, collecting CAN bus data, proprietary powertrain, CAV sensor data, and GPS – 60+ signals at 1Hz. The fleet consists of vehicles with GM SuperCruise automated technology: Cadillac CT4, CT5, Escalade, and Chevy Bolt. The data will be used to

- Develop and validate the SuperCruise model in RoadRunner.
- Understand scenario definitions for CAV technology usage.
- Quantify the energy impacts of automation supported by a thorough analysis of the data.
- Eventually propose a methodology for the real-world benefits of CAV.

Argonne has laid the groundwork to receive, take in, process, store, access, and analyze the data efficiently.

We processed and analyzed several weeks of driving data for quality. We developed tableau dashboards to allow for real-time driving and signal visualization. Map matching was performed with HERE API to extract road information as a data augmentation step (e.g., extract speed limit, traffic pattern information, traffic signs, slope, etc.). Another data augmentation layer involved the decoding of vehicle identification numbers (VINs) for all the vehicles in the fleet. We used the Autonomie Vehicle Information Database (AuVID) to extract detailed vehicle specifications to enrich raw driving data with vehicle details. We generated summary level data analysis reports to analyze data distributions and quantile and descriptive statistics, observe correlations, and detect outliers. We plan to continue the incoming flow of data in FY22 as 500+ Gb of driving data are anticipated.

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 first year of a planned three-year project, we made major inroads towards these goals.

We expanded the capabilities of the controls originally developed in SMART 1.0 and demonstrated greater energy savings. We developed two new V2X use cases. Information from preceding vehicles can be transmitted via V2V and used to estimate the speed of the immediately preceding vehicle, leading to up to 6% in additional energy savings. In another application of V2X, we improved the V2I-enabled eco-approach module to consider all incoming traffic signals for which it receives information, not just the one signal. This enhancement can result in up to an additional 15% of energy savings.

Another way to improve energy savings is to use the power of AI. We created a first prototype of an AI module that is integrated within the eco-driving controls and that can adjust the calibrations dynamically during the drive and demonstrated energy savings of up to an additional 12%. We also created the new "powertrain-aware" control that considers the powertrain and directly minimizes its energy consumption, but only controls the speed of the vehicle. It sits between our existing controls "speed-only" and "speed+powertrain" in terms of the energy savings vs. complexity trade-off. The first results show up to 3% additional energy savings compared to speed-only. Finally, we also improved the robustness of our controls in traffic situations, which is essential to ensure the feasibility of these controls in real-life applications.

One great novelty of this project compared to the SMART 1.0 is the goal to exit the confines of simulation and test the controls in real vehicles. In Year One of the project, we achieved great success: for the first time, we demonstrated eco-driving controls in XIL on three different vehicle platforms, both on chassis dynamometer and on track despite COVID-related work restrictions. This success is attributable to the thorough preparation of controls in simulation, using digital twins of the vehicles and of the scenarios, before moving to functionality testing and full-blown testing. Argonne's XIL workflow, developed as part of another SMART 2.0 project and a Core Tools project, was also critical; it enabled us to quickly move between pure simulation and dynamometer testing, leading to over 700 km worth of useful tests.

On the chassis dynamometer, we demonstrated energy savings of up to 22% when the eco-driving control is applied to an electric vehicle (Chevrolet Bolt) in a variety of situations, including traffic signals, speed limit changes, V2I-enabled eco-approach, and preceding virtual vehicles. The control was integrated within our partners MTU/ACM's vehicles and successfully tested on track in similar scenarios (single vehicle only, no real/virtual preceding vehicle). We also initiated work on a third XIL testing framework with our partners at Clemson, in which real vehicles equipped with Argonne's controls will be tested on track with virtual vehicles simulated in a traffic flow simulator. In FY21, we performed software-in-the-loop (SIL) testing of the concept, showing promising results.

Finally, we initiated our collaboration with CRADA partner GM, establishing a data pipeline where hundreds of gigabytes of data coming from GM's fleet vehicles equipped with driving automation are shared and analyzed at Argonne. This will help us guide the development of a methodology for estimation of energy savings of CAVs.

In the next two years, expected outcomes will include

- Maturation of concepts imitated in FY21, such as AI or the "powertrain-aware" control.
- Greater inclusion of traffic scenarios in simulations.
- Expansion of dynamometer XIL to more vehicle platforms, controls, and scenarios.
- Completion of track testing at ACM.
- Demonstration of our controls in traffic conditions (with Clemson University) and in L3 automated vehicles (USF).
- Analysis of GM's real-world data, model development, and creation of a CAV energy benefits methodology.

Key Publications

1. Gupta, Shobhit, Daliang Shen, and Dominik Karbowski. 2022. "Data-Driven Koopman Model Predictive Control for Eco-Driving of Automated Vehicles." Submitted to IEEE American Control Conference. Atlanta, Georgia.

2. Han, Jihun, Dominik Karbowski, and Aymeric Rousseau. 2020. "State-Constrained Optimal Solutions for Safe Eco-Approach and Departure at Signalized Intersections." In *ASME 2020 Dynamic Systems and Control Conference*. Pittsburgh, Pennsylvania. https://doi.org/10.1115/DSCC2020-3150.

3. Han, Jihun, Woong Lee, Dominik Karbowski, Aymeric Rousseau, and Namwook Kim. 2020. "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. https://doi.org/10.1109/VPPC49601.2020.9330831.

4. Han, Jihun, Daliang Shen, Dominik Karbowski, and Aymeric Rousseau. 2020. "Leveraging Multiple Connected Traffic Light Signals in an Energy-Efficient Speed Planner." *IEEE Control Systems Letters* 5 (6): 2078–83. https://doi.org/10.1109/LCSYS.2020.3047605.

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6. Lee, Woong, Jihun Han, Yaozhong Zhang, Dominik Karbowski, Aymeric Rousseau, and Namwook Kim. 2021. "A Real-Time Intelligent Speed Optimization Planner Using Reinforcement Learning." *SAE Technical Paper 2021-01-0434*. https://doi.org/10.4271/2021-01-0434.

7. Shen, Daliang, Dominik Karbowski, and Aymeric Rousseau. 2020. "Solving Eco-Driving Problems Using Indirect Collocation Method and Smooth Representation." *IEEE Control Systems Letters* 5 (5): 1501–6. https://doi.org/10.1109/LCSYS.2020.3040690.

8. *Manuscripts here: www.zotero.org/groups/2254223/argonne_vehicle_and_mobility_systems_publications.*

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2. Han, Jihun, Dominik Karbowski, and Namdoo Kim. 2020. "Closed-Form Solutions for a Real-Time Energy-Optimal and Collision-Free Speed Planner with Limited Information." In *2020 American Control Conference (ACC)*. Denver, Colorado. https://doi.org/10.23919/ACC45564.2020.9147382.

3. Karbowski, Dominik, Daliang Shen, Jihun Han, Jeong Jongryeol, and Namdoo Kim. 2020. "Eco-Driving: Energy-Focused CAV Control Development." In *SMART Mobility Connected and Automated Vehicles Capstone Report*, 122–47.

4. Shen, Daliang, Jihun Han, Jongryeol Jeong, Dominik Karbowski, and Aymeric Rousseau. 2020. "Receding Horizon Reference Governor for Implementable Optimal Powertrain-Aware Eco-Driving." In *IFAC World Congress*, 8. Berlin: Elsevier.

5. Shirokinskiy, Konstantin, Wolfgang Bernhart, and Stephan Keese. 2021. "Advanced Driver-Assistance Systems: A Ubiquitous Technology for the Future of Vehicles." Roland Berger. March 31, 2021. https://www.rolandberger.com/en/Insights/Publications/Advanced-Driver-Assistance-Systems-A-ubiquitous-technology-for-the-future-of.html.

Acknowledgments

Argonne researchers: Jihun Han, Daliang Shen, Jongryeol Jeong, Yaozhong Zhang, Ayman Moawad, Miriam di Russo, Kevin Stutenberg, Eunjeong Hyeon, Woong Lee, and Shobhit Gupta. University project partners: Ardalan Vahidi, Tyler Ard (Clemson University), and Vadim Sokolov (George Mason University). CRADA partners: Jeremy Wise, William Dvorkin, and Matt Zebiak (GM). Collaborators: Jeff Naber and Ahammad Basha Dudekula (Michigan Tech University).

I.1.2 Characterizing Behaviors and Capabilities for Emerging Connected and Automated Vehicle Technologies, Sensors, and Connectivity (Argonne National Laboratory, National Renewable Energy Laboratory)

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Start Date: September 1, 2020 End Date: September 30, 2023
Project Funding: $743,000 DOE share: $743,000 Non-DOE share: $0

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 Connected and Automated Vehicle (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 like the 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 and Connectivity Performance) is to provide detailed CAV sensor and connectivity 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, latency, etc.) for a range of CAV sensing and connectivity 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.1.2.1 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.

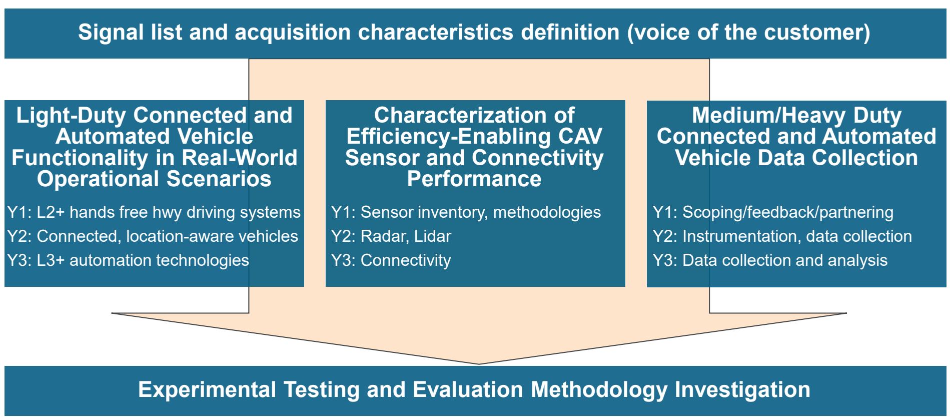

Figure I.1.2.1 Visualization of the Characterizing Behaviors and Capabilities for Emerging Connected and Automated Vehicle Technologies, Sensors, and Connectivity project approach

The LD data collection leverages a mobile data collection platform developed as part of the 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 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

Signal Data Definition

The first deliverable and logical starting point in the LD CAVs data collection task was defining the required signals to be collected that will comprise the main deliverable for year 1 of the project. By collaborating with modeling staff and assessing the type of sensors and perception systems we have available, a list of signals was generated. This is shown in Table I.1.2.1. This list establishes all the requirements for the hardware, perception parameters, real-time data collection, and post-processing efforts for the rest of the FY.

Table I.1.2.1 LD CAV Data Collection Signal List

Test Vehicle Data		Adjacent Vehicle Data	
Position	GPS location and distance since start	**Track #**	Each vehicle assigned ID, all have data below
Speed	GPS and veh CAN	**Relative Lane**	-1 = one lane over left, 2 = 2 lanes over right
Accel pedal %	Veh CAN	**Relative position**	x,y pos in meters referenced front ego vehicle
Brake	on/off and/or brake % from veh CAN	**Speed**	post processed from LIDAR data
Turn Signal	left/right/off	**Acceleration**	post processed from LIDAR data
Steering Angle	Veh CAN	**Brake status**	if possible
Wiper on/weather info	Veh CAN and/or driver notes on weather	**Turn signal status**	if possible
ADAS feature enabled	Veh CAN and/or driver notes	**Vehicle type**	car, large car, truck, semi (from vision system)
ADAS speed target	Veh CAN and/or driver notes	**Vehicle length**	from vision system
ADAS gap target	Veh CAN and/or driver notes	**merge lane change info**	distance to forced lane change, on-ramp/off-ramp need some discussion
Lead vehicle gap	stock or external radar used	**Roadway Data**	
Lead vehicle speed	stock or external radar used	**Roadway name**	post processed from GPS location
Lead vehicle acceleration	stock or external radar used	**Functional classification**	Interstate, Major/Minor Arterial, Major/Minor Collector etc
Eng RPM	Veh CAN	**Number of lanes**	#
Eng load or torque	Veh CAN %load or torque in Nm	**Elevation**	from GPS
Gear #	Veh CAN	**Traffic density**	from vision and/or scraped from traffic data
other powertrain data	whatever we have from CAN bus on that particular vehicle	**Local traffic speed**	from vehicle speed & vision
		Distance to next stop	post processed from GPS location
		Type of next stop	NoTurn/Turn, Stopsign/Stoplight/None

Perception Hardware and Software

To perceive the vehicles around the test vehicle, a sophisticated traffic environment perception kit had to be developed and installed on the test vehicles. The data acquisition system is comprised of off-the-shelf elements along with other data collection systems for vehicle powertrain data. The system collects data from 1) the vehicle CAN bus, 2) a front-facing radar, 3) a 32-line LIDAR, 4) five cameras, 5) a 360-degree action camera. The system can identify vehicles using the cameras and object location is perceived by the LIDAR. The data is all collected and fused by an industrial Linux PC. Figure I.1.2.2 shows the system installed on the CT6 SuperCruise test car.

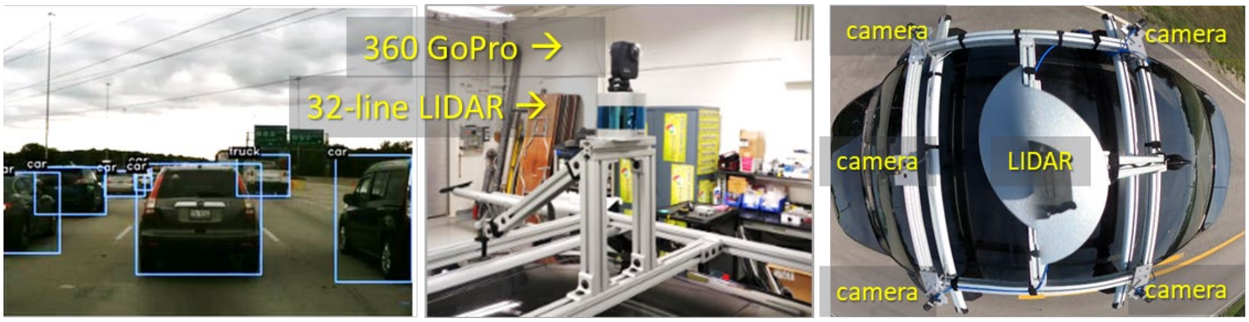

Figure I.1.2.2 At left: Perception system classifying objects, at center: LIDAR and 360-degree camera, at right: view of roof rack on which sensors are mounted

Tuning and Data Collection

A significant amount of effort was directed to system integration and performance tuning for our application. After testing several iterations of settings, a balance was struck between the amount of processing that was performed by the data acquisition system at run-time processing and the amount of post-processing. Figure I.1.2.3 shows a screen capture of the perception kit software with bounding boxes around the clusters of LIDAR hits perceived as vehicle objects. By filtering out objects not in the neighboring lanes, the surrounding vehicle positions and sizes can be classified and sorted into a final data file. The 360-degree video is anonymized (sufficient down-resolution and blurring of faces and license plate) and time aligned with the data so a future researcher can get better context of the data streams at any given time.

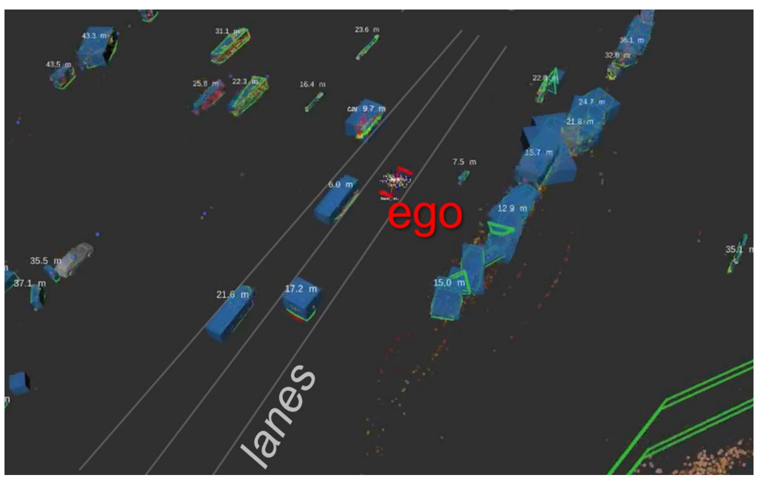

Figure I.1.2.3 Screen capture of mobile perception system identifying vehicles around the “ego” test vehicle during testing.

In FY 21, as expected there were a few delays early on, both due to supply chain delays in receiving hardware and reduced early activity in the lab due to the COVID-19 pandemic. As of the end of September, the system is in operation pursuant to the goal of collecting practical, real-world autonomous driving data for both the Cadillac CT6 “SuperCruise” system and the Tesla Model 3 “Autopilot” system. By the end of the calendar year, we expect 1,000 miles of data (each) for both test vehicles available to the research community.

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

Medium and Heavy Duty Connected and Automated Vehicle Stakeholder Feedback

The first deliverable in the MD/HD CAVs data collection effort was to reach out to a diverse group of stakeholders in the MD/HD CAVs space and users of the to-be-collected data to prioritize the data needs and understand how CAVs are currently perceived. The feedback farm had 16 questions on 13 technology types/levels of automation and 12 different situational scenarios. Forty total responses were received with at least 4 from each group: Truck producer, CAV technology producer, Fleet operator, Government/regulator, and Non-Governmental Organization/Policy advocate. A draft report was written, and results presented to multiple audiences.

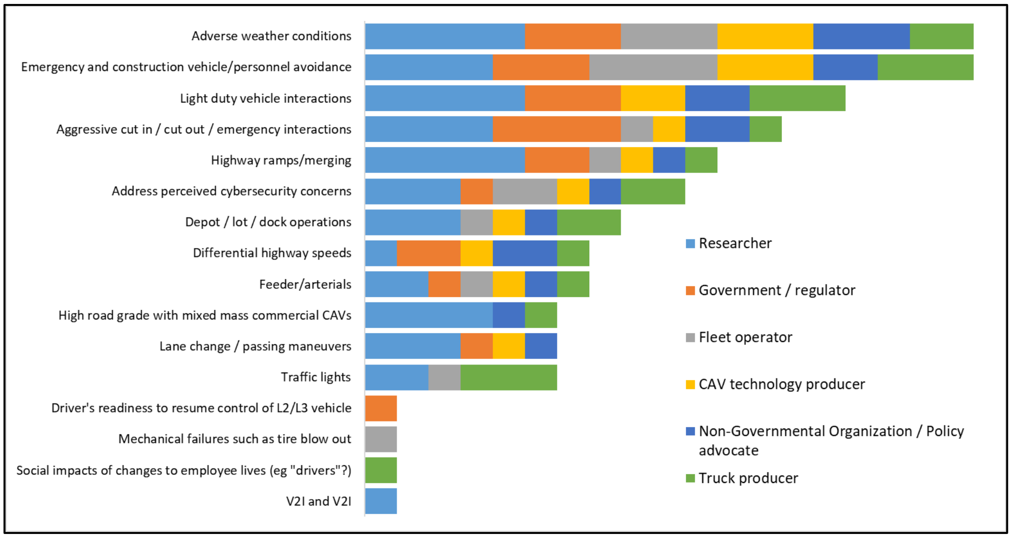

Figure I.1.2.4 Question 9 respondent breakdown results – Situations most in need of study to bring CAV technologies emerging in the next 3-10 years to widespread adoption.

Some specific conclusions include:

- Overall, the lower levels of CAV technologies were seen to still have improvement opportunities or research needs and should not be ignored.
- Researchers and Truck producers are more optimistic on fleet readiness to adopt higher levels of automation technologies than fleet respondents.
- Driver acceptance might be a significant hurdle to overcome for widespread adoption.
- Researchers might be over prioritizing research needs of several situations including “aggressive cut in/cut out/emergency interactions” and “lane changes and passing maneuvers”, but that does not mean they fall completely off the priority list.
- The situational priority list for non-researcher stakeholder includes:
    - Adverse weather conditions
    - Emergency and construction vehicle/personnel avoidance
    - Light duty vehicle interactions
    - Highway ramps/merging
    - Aggressive cut in/cut out/emergency interaction.

Vehicle Data Collection Partnerships

NREL does not own MD/HD test vehicles and as such is dependent on partnering with outside parties who own and operate MD/HD CAVs of interest and are willing to work with NREL and share collected data with the research community. Significant effort has gone into talking to possible partners and getting to committed agreements. Several early prospective partners have either backed out temporarily or legal agreements are difficult to achieve. NREL has secured two partnerships so far during the 4th quarter of the first project year.

Cummins Inc agreed to participate in this project at the end of July. This data collection task will build off an existing DOE FOA project on Truck Platooning with ADAS features. Early data sharing of past test runs began in August and further data sharing from ongoing activities began in September. Data for over 30 test days from baseline, two-truck-platoons and three-truck-platoons were shared at the end of the fiscal year; all data sharing included forward facing radar raw and identified target signals. Four days of forwarded facing video camera data was also shared and more is available pending usefulness of the file format available.

Locomation agreed to work with NREL at the end of September and planning is underway for testing and data collection of their SAE L4/5 truck follower platooning system. Data from cameras, LIDAR, and radar will be collected in a single ROS bag file with some J1939 channels. Initial sample data will be provided in 1Q22 with a on public road-testing series planned for 3Q22.

Task 3 CAV Sensor and Connectivity Performance

Sensors

Perhaps one of the most important aspects of the sensor and connectivity performance task was the choice of sensors to be evaluated. With a focus on the most relevant sensors for CAVs, we have acquired a range of different radar and LIDAR and camera sensors, representative of the best currently available options. The list of sensors includes a short- and long-range radar, a short, medium and long-range LIDAR, and single camera with multiple lens options. More detailed sensor specifications are shown in Table I.1.2.2.

Table I.1.2.2 List of Sensors and Corresponding Specifications to be Used for Sensor Characterization

Sensor	Make/Model	Range [m]	FoV [H°xV°]	DAQ Method
RADAR	Delphi SRR2	80	150 x 10	CAN
RADAR	Delphi ESR2.5	175	20 x 4.75	CAN
LIDAR	Ibeo Lux 4L	50	110 x 3.2	Autoware AI
LIDAR	Velodyne Puck	100	360 x 30	Autoware AI
LIDAR	Velodyne Ultra Puck	200	360 x 40	Autoware AI
CAMERA	FLIR Blackfly S GigE BFLY-PGE-20E4C-CS	-	-	Autoware AI

Data Acquisition System

Following the list of sensors to be tested, the next most import step was to set-up a data acquisition system for capturing and storing data from the various sensors. The different sensors all have their own data output format. The radar sensors output CAN bus data which will be collected with automotive CAN data acquisition hardware. The LIDAR and camera sensors output raw data via Ethernet connection and will be acquired using the open source Autoware software which stores the data into a ROSBAG file format. A significant amount of effort during the first year of this project was spent on successfully getting the Autoware software to work with the three specific LIDAR sensors and the camera system we have chosen. The Autoware software was set-up to simultaneously collect data from all the LIDAR and camera sensors and store the data into a single ROSBAG data file.

Test Planning

With the sensors and data acquisition system set-up, the next step was to come up with a test plan for collecting data which can be used to characterize the performance of the various sensors. This included making the decisions on what sensor performance characteristics are of interest and how do we evaluate them most effectively. To help with figuring out what sensor performance characteristics are of interest, we held discussions with Argonne's modeling and simulation team working on *Development and Validation of Intelligent CAV Controls for Energy-Efficiency* and came up with a list of sensor performance metrics which are necessary for modeling of the sensors.

For the question of how we test the sensors, there were multiple options that we considered. Some of these options included installing all the sensors on a vehicle and drive it around to collect sensor data with other vehicles and objects on the road, or with a target lead vehicle which is also instrumented with at least a high-accuracy GPS and vehicle data acquisition system. Two other options were to mount the sensors to a vehicle and drive it toward stationary target objects or mount all CAV sensors on a portable test platform and collect the sensor data from a fixed location with stationary target objects. It was finally decided to go with the fourth option, collecting sensor data from a fixed location with stationary target objects to maximize test-to-test repeatability, getting higher accuracy ground truth measurements and sensor accuracy calculations, and having the lowest complexity test set-up.

Testing Progress

After narrowing down the test plans for the sensor performance characterization, we have since found a suitable outdoor area on the Argonne campus for carrying out the sensor testing. In addition to this, we have successfully constructed a first version of the portable test platform for mounting, leveling, and aligning the various sensors. Finally, we have performed a dry run experiment and collected a first set of data for the long-range radar sensor. This first experiment served multiple purposes, including verifying the practicality of the test platform for aiming sensors and testing their entire field of view, as well as gaining an understanding of the target object placement accuracy that is possible with our test set-up. Lessons learned from this dry run experiment will also help refine test plans and testing procedures for larger data collection efforts. An image from the dry run data collection experiment is shown in Figure I.1.2.5.

Figure I.1.2.5 Dry run of sensor characterization data collection set-up on ANL campus

Task 4 Experimental Testing and Evaluation Methodology Investigation

Challenges

Relevant stakeholder activity in the space of testing CAVs for fuel economy and emissions is overshadowed by the abundant activity in safety and reliability testing. However, some progress has been made in focusing of test procedures for vehicle efficiency. The objective is to continue running these efficiency (and emissions) tests in a chassis dynamometer laboratory that precisely controls road loads and environmental conditions for repeatable test results (as compared to on-road or on-track testing). A few preliminary meetings of an SAE task force (within the same group responsible for vehicle fuel economy/emissions testing procedures) held discussions centered on the challenges to address in the task force. They are:

- For what level of autonomy are new test methods needed (SAE Levels 3-5 are assumed)?

- What tests will not be possible by virtue of missing traditional vehicle controls (steering wheel, accelerator, etc.)?
- OEMs can tie into proprietary vehicle controls. How might non-OEM labs test CAVs missing traditional controls?
- Do we need completely new procedures? Or can we design adjustment factors for existing test methods?

In this effort, ANL staff has begun scoping out the testing landscape by devising three testing framework types to use as discussions continue forward.

1) *New Drive Trace*
This is the least disruptive change in the testing approach. The test vehicle drives a modified speed-time trace whereas the remainder of the test procedures and laboratory hardware are used in a traditional fashion. The speed-time trace represents the speeds at which the test vehicle drives (while in autonomous driving mode) if it were following a vehicle that is driving the prescribed EPA time-speed trace. For each vehicle, a new drive trace must be generated that represents the test vehicle following a vehicle driving the trace. Required for this type of testing is a full understanding of the test car controls and dynamics in response to a lead vehicle to generate the trace.

2) *Sensor Spoofing*
This next approach follows the same assumption as above, that the test represents driving behind a vehicle that is driving the actual test drive cycle. In this case, the vehicle reacts in real time to sensor data emulated by a computer representing a lead vehicle driving the speed cycle.

3) *VIL with Standard Interface*
If the CAV possesses connectivity or perception of the environment/other vehicles, there needs to be a way to account for all the decisions made by the vehicle in addition to its longitudinal controls. This approach requires a paradigm shift from a test that prescribes a simple time-speed trace test, to one that prescribes a driving trip over a route rich with features with which the CAV would react and interact. This would require a high-speed data bus connection from the vehicle to an emulation computer that tracks the vehicle in a "micro-simulation" environment (what is referred to as Vehicle-In-the-Loop [VIL] testing). The type and amount of data is to be determined. The model isn't very different from other SAE standards that prescribe connections for recharging plug-in electric vehicles or other diagnostic communication standards that prescribe use cases and message IDs.

Conclusions

Task 1 (Light-Duty [LD] CAV Functionality in Real-World Operational Scenarios) successfully achieved the goal of developing and integrating a perception kit capable of collecting the data to provide the context required to characterize the behavior of advanced production autonomous driving vehicle systems. The data is organized so that researchers can analyze the behavior of current technology when designing future systems that aim to achieve the overall goals of the DOE EEMS program.

Task 2 (Medium/Heavy Duty [MD/HD] Connected and Automated Vehicle Data Collection) successfully completed the stakeholder feedback effort to prioritize activities for the primary vehicle data collection. Partnerships with two 3rd parties for data collection have been formalized and data collection initiated with the first partnership and planning underway with the second. Additional partners are still considering participation and others are being sought.

Task 3 (CAV Sensor and Connectivity Performance) has prepared well for successfully meeting its milestones in FY2022. During FY2021, we have acquired all the desired sensors, DAQ hardware, and developed the DAQ software for data collection from the wide variety of selected sensors. Experimental design and test planning were completed in collaboration with Argonne's modeling and simulation team working on *Development and*

Validation of Intelligent CAV Controls for Energy-Efficiency to ensure relevant sensor data is collected. Finally, initial dry run experiments have provided valuable lessons learned for testing refinement in FY2022.

Task 4 (Experimental Testing and Evaluation Methodology Investigation) has resulted in a sound foundation of testing frameworks that will help propel the development of future chassis dynamometer test procedures for CAVs. The adage "you can only improve what you can measure" suitably summarizes the importance of this work seeking to develop unified and accurate test procedures in preparation of future, advanced energy efficient CAVs.

References

1. SAE J3016, Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles, DOI: https://doi.org/10.4271/J3016_202104

I.1.3 BEAM CORE (NREL; LBNL)

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Start Date: October 1, 2020 End Date: September 30, 2023
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Project Introduction

Starting in 2016, researchers at Lawrence Berkeley National Laboratory (Berkeley Lab), along with collaborators from National Renewable Energy Laboratory (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, including private vehicles, all forms of public transit, active modes like walking and biking, as well as more innovative services such as ride-hailing (provided by transportation network companies [TNCs]) and micro-mobility ('dockless' shared bike, e-bikes, and e-scooters). BEAM integrates with cutting edge tools developed at NREL, including ADOPT, FASTSim, and RouteE, which enable BEAM to simulate a comprehensive set of emerging vehicle innovations, such as electrification and automation, with a highly resolved ability to model 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, bus 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. Results from these scenario analyses include a suite of output metrics such as aggregate vehicle and person miles traveled, vehicle hours traveled, congestion, energy consumption, and the comprehensive Mobility, Energy, Productivity (MEP) metric developed by NREL as a combined accessibility-based measure capturing impacts to potential mobility and system energy consumption. This integration between BEAM, ADOPT, FASTSim, RouteE, UrbanSim, and MEP was previously referred to as the BEAM-centric SMART Mobility Workflow.

In fiscal year (FY) 2021, Berkeley Lab researchers, together with their NREL and UrbanSim team-members, began the development of the next generation of this integrated modeling framework, by increasing the integration of sub-models, improving simulation capability, and enhancing computational performance. The suite of integrated models is now to be known collectively as the BEAM Comprehensive Regional Evaluator, or BEAM CORE.

Objectives

Objective 1: Increased integration, automation, and improved algorithms mean faster run times and more efficiency, enabling more ambitious scenario analyses and wider applicability (Task 1) – Increased automation, coupled with faster road and transit network assignment and routing algorithms, and increased parallelization, are expected to result in short-run scenario run times reduced by 30% by September 2021 relative to SMART 1.0, and by 60% by September 2023. Long-run scenarios involving the full BEAM CORE integration between BEAM and UrbanSim are expected to see run time reductions of 70% by September of 2023. BEAM CORE will be implemented on Berkeley Lab's NERSC high-performance computing facility, which will further decrease runtime and allow for large numbers of scenario analyses to be launched in parallel.

Objective 2: BEAM CORE will be deployed to multiple new regions, increasing the value of BEAM CORE to an increasingly expanding number of stakeholders, and enabling a better understanding of transportation system and technology scenario impacts across different types of regions (Task 1) – BEAM CORE, in contrast to similar integrated models of this scale and complexity, can be deployed in a new region relatively efficiently. BEAM, and its integration with the current component models of BEAM CORE, is currently implemented in some form in the San Francisco Bay Area, Detroit, Austin, and New York City regions. Over the course of the next two years the base-level of BEAM will be implemented in six additional regions with varying degrees of BEAM CORE functionality.

Objective 3: BEAM CORE will specialize in long-term scenario analyses with dynamic and nuanced realism in regional population and economic behavioral evolution, and new capabilities will mean a wider set of questions that can be answered by BEAM CORE and increased value to a wider set of stakeholders (Task 2 and 3) – A strength of BEAM CORE is simulating realistic behaviors of individual travelers. This emphasis will be taken to a new level, as BEAM CORE will integrate a sophisticated set of modules modeling realistic lifecycle evolution of households (in Demographic Microsimulation [DEMOS]) and firms (in the Business Activity and Mobility Simulator [BAMOS] module of Freight Activity Mobility Simulator [FAMOS]) over time, in response to shifts in transportation system performance and the built environment. FAMOS enables modeling of freight delivery in BEAM CORE, including freight demand generation (including e-commerce demand), delivery planning, and delivery activity in the transportation system. Automobile and Technology Lifecycle-Based Assignment (ATLAS) is a new vehicle transaction and technology adoption model, which will make vehicle and technology ownership decisions of households sensitive to lifecycle phases and related dynamics. ATLAS, which focuses on household-specific vehicle allocation and decisions, will integrate with the ADOPT model, which captures how emerging vehicle technologies mature and penetrate the market. In addition, BEAM CORE is building in a new set of capabilities to enable detailed **dynamic curb-space allocation and modeling of related management scenarios** to evaluate different policies and scenarios to manage access to the curb. Finally, as transit agencies face increasingly complicated challenges, BEAM CORE will enable simulation of **transit system** adjustment to demand shifts.

Objective 4: Tools and actionable insights straight into the hands of stakeholders (Task 4) – The work on BEAM CORE during this three-year research phase will be highly informed and guided by stakeholder input and will culminate 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. A series of reports and presentations will be prepared to document critical insights that can only be gleaned from such a comprehensive integrated modeling environment. A comprehensive set of sensitivity analyses will capture the marginal impacts of the individual levers that shift critical outcomes in the transportation system. Deep-dive research efforts will focus on specific critical issues including the impacts on transit systems in the SF Bay Area.

Approach

BEAM CORE integrated model configuration and structure is depicted in Figure I.1.3.1.

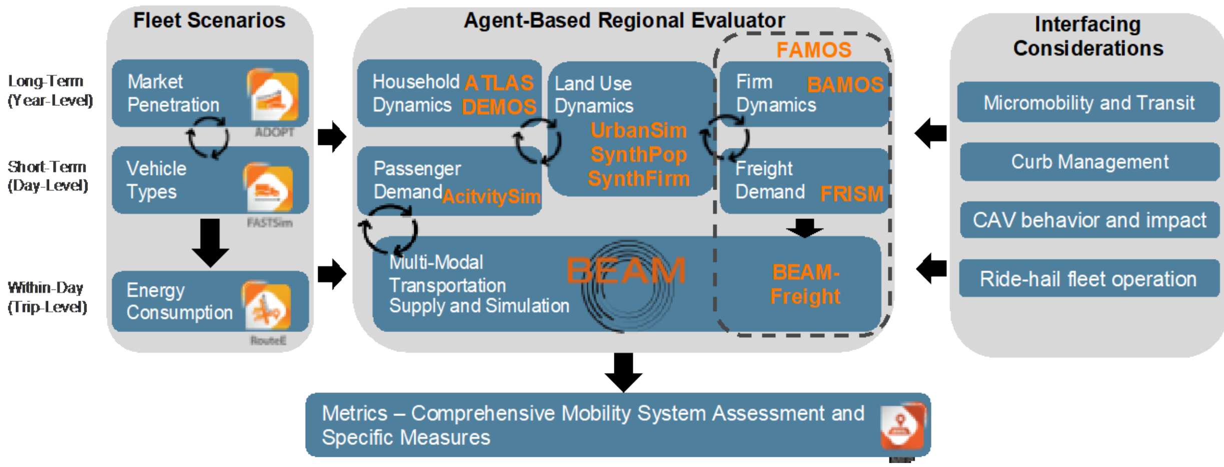

Figure I.1.3.1 BEAM CORE Integrated Model Structure

BEAM CORE development is organized into four tasks:

Task 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 to six new regions.

Task 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.

Task 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 in versions v1 and v2 of this simulator (which includes SynthFirm, FRISM [Freight Integrated Simulation Model], and BEAM-Freight), and in v3, long-term dynamics of freight elements that include firm lifecycle and supply chain formation and evolution as captured through dynamic extension of FRISM and BAMOS, which evolves the initial baseline synthetic firm population from SynthFirm dynamically over time.

Task 4: Application and Outreach – concerted stakeholder engagement; design and execution of design of experiments sensitivity analyses of BEAM CORE; design and development of BEAM CORE ACT; and deep-dive analyses of key research topics to generate actionable insights from BEAM CORE.

Results

Objective 1: A full integration between land use (UrbanSim), activity planning (ActivitySim), and transport network simulation (BEAM) models has been completed, enabling automated runs. New capabilities in the ActivitySim-BEAM linkage have been enabled, including a richer set of non-work activity choices, high-occupancy vehicle car trips, and multi-modal trips. BEAM and ActivitySim has been fully integrated through ActivitySim Light, which enables automated pass-off between ActivitySim's mode choice model and BEAM's network simulation between iterations such that the mode-choice of the demand side of the model comes into equilibrium with the network simulation within each simulation run. Even as these new complexities have been added to the model, target run-time reductions of 30% have been exceeded. Runs are completing in ~50% the time of runs at the end of SMART 1.0 with 50% higher population. In addition, a benchmarking exercise (Figure I.1.3.2) revealed that running on a 40% sample captures most of the accuracy at approximately a third the run time of a full sample, providing context for understanding trade-offs between simulation population sample size and run-times.

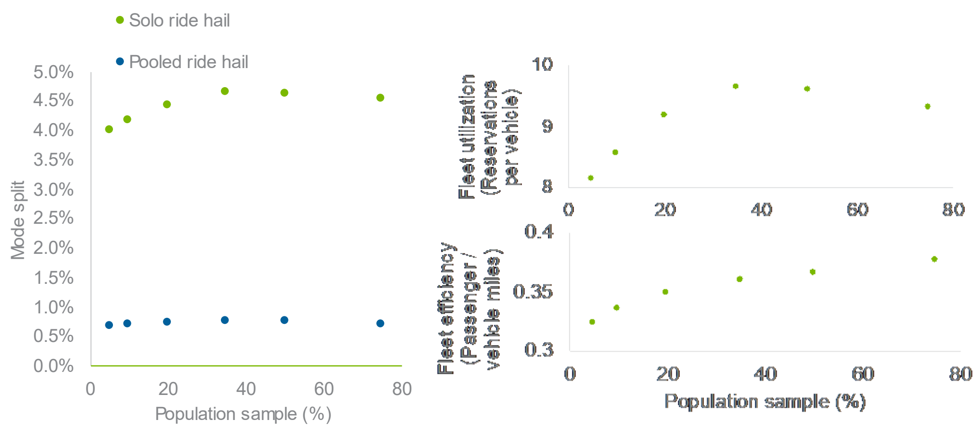

Figure I.1.3.2 Model Performance of Ridehail Scenarios in Austin by Population Sample Size

<u>Objective 2:</u> In addition to gaining insight on stakeholder priorities, stakeholder engagements during this FY informed the development of the working plan for BEAM CORE deployment over the next two years. Beyond the four regions that currently have some level of BEAM deployment, six new regions have been identified for priority deployment: Seattle, WA; Eugene-Springfield, OR; Washington, DC; Kansas City, KS/MO; Denver, CO; and Jacksonville, FL.

<u>Objective 3:</u>

Progress on DEMOS: the DEMOS model has been built from scratch and consists of a series of connected modules governing the various dynamic lifecycle transitions of individuals and households. All modules pertaining to migration, and individual-level evolution (other than employment) have been estimated and completed (see blue checkmarks in Figure I.1.3.3), and progress has been made formulating the approach to estimate the employment, household formation and longer-term household choice models.

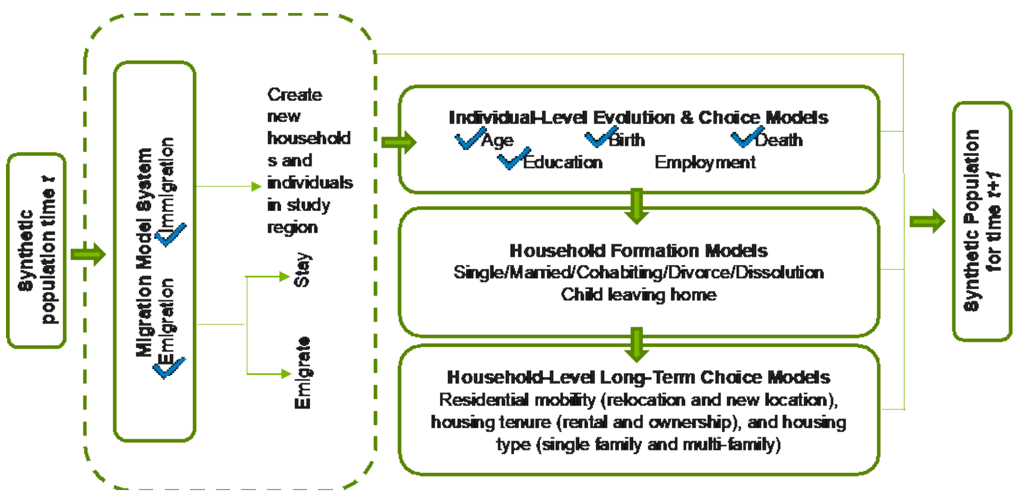

Figure I.1.3.3 DEMOS Model Architecture and Progress

Progress on ATLAS: The ATLAS model consists of multiple interconnected modules capturing both static vehicle assignment and dynamic household transaction decisions. The model architecture is shown in Figure I.1.3.4. The full set of capabilities have been estimated. The static version of ATLAS capturing vehicle assignment has been fully calibrated, validated and implemented. The initial choice model for dynamic transaction decisions (ATLAS v2) is estimated but not yet implemented or validated, as it depends on the outputs from some of the dynamic household evolution modules in DEMOS that are not yet complete.

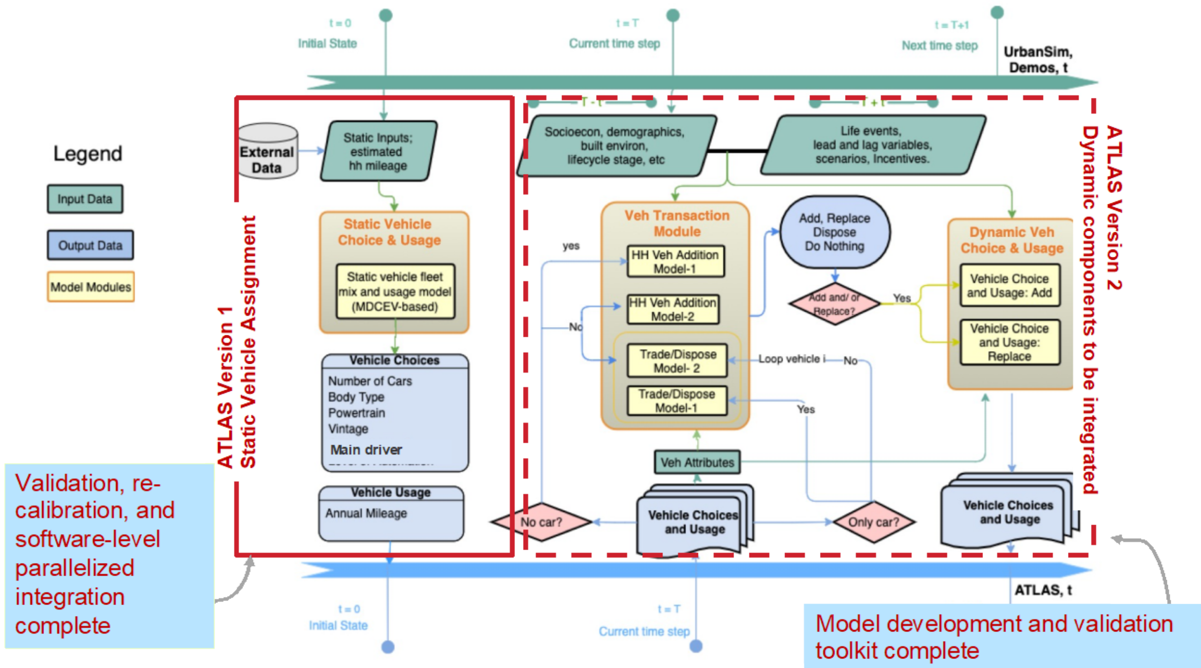

Figure I.1.3.4 ATLAS Model Architecture and Progress

Progress on Freight (FAMOS): The FAMOS modeling capabilities include a near-term static complete freight firm synthesis, demand generation, and network simulation integrated framework (Figure I.1.3.5 and Figure I.1.3.6). The SynthFirm and FRISM modules are operational for the SF Bay Area region, with business-to-business (B2B) and business-to-consumer (B2C) generation results validated and calibrated to observed trends for the 2017 baseline. BEAM-Freight is implemented in the SF Bay Area and being validated.

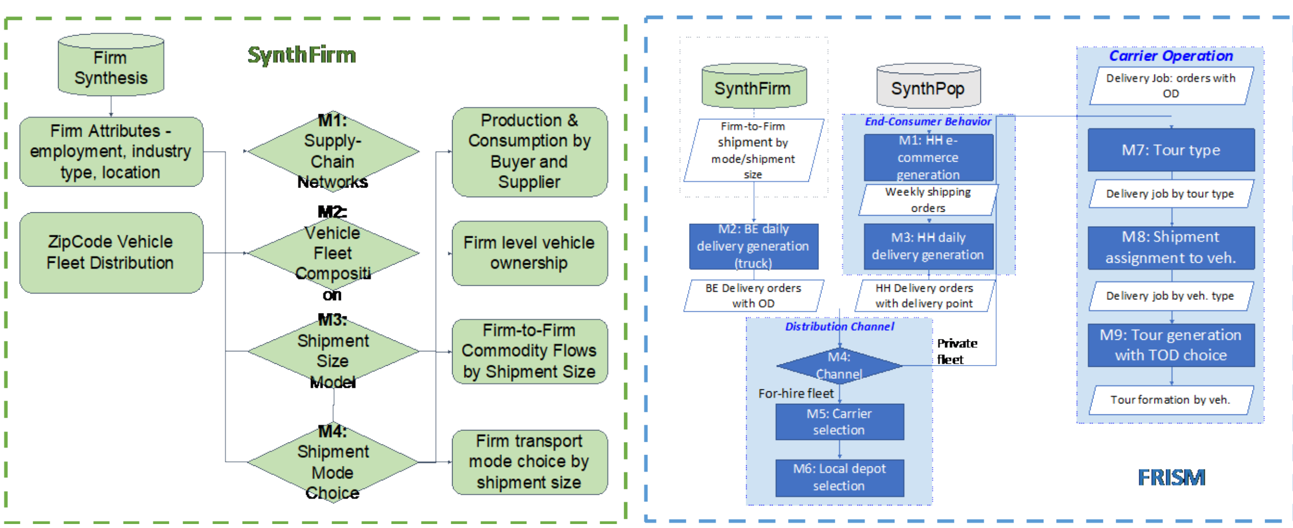

Figure I.1.3.5 FAMOS Model Architecture: SinthFirm & FRISM

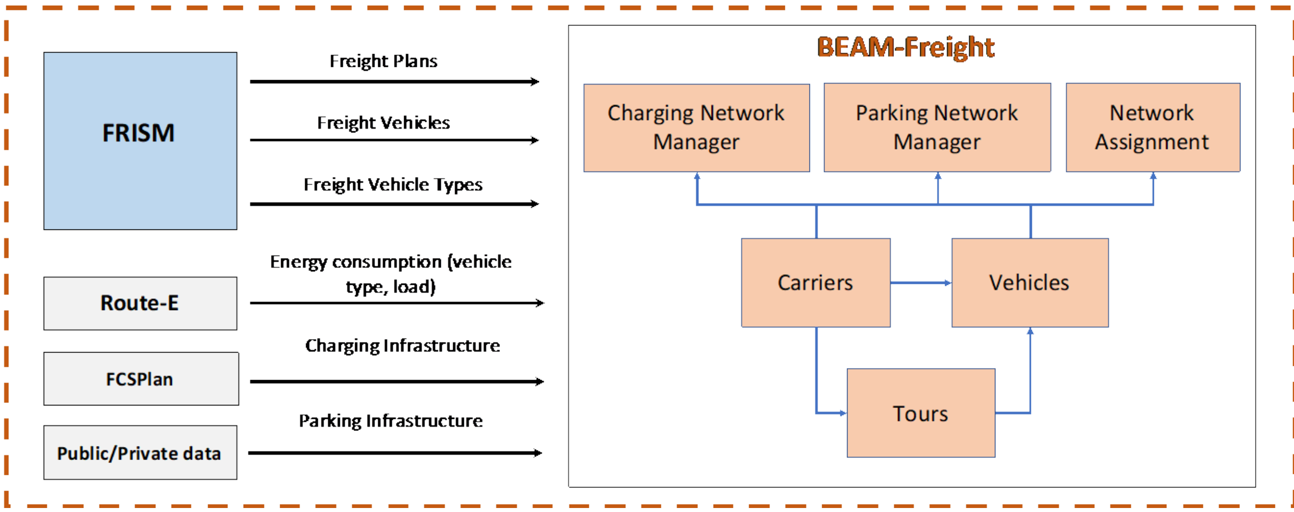

Figure I.1.3.6 FAMOS Model Architecture: BEAM-Freight

Objective 4:

Progress on Stakeholder Engagement: During fiscal year 2021 the BEAM CORE stakeholder engagement effort conducted 25 direct engagements with different groups of stakeholders including metropolitan planning organizations (MPOs), city planners, departments of the environment, transportation authorities, transit agencies, academic researchers, private industry, and more, in 12 regions across 10 different states.

Progress on design of experiments: The design of the sensitivity analysis plan, including priority levers to assess marginal effects, and overarching scenarios, has been completed.

Progress on BEAM CORE ACT: An initial implementation of BEAM CORE ACT has been created and populated with data for demonstration purposes.

Progress on Deep Dive Analyses: Design of priority studies for deep dive analysis have been completed.

Conclusions

BEAM CORE performance improvements have resulted in run time efficiency gains that exceed expectation, and all model refinement and development are on track. Development of new modules, DEMOS, ATLAS, and FAMOS, reflect significant progress over this year, with modules poised to be fully integrated into the BEAM CORE workflow. Significant stakeholder engagement efforts have expanded awareness of BEAM CORE to a wide range of interested parties, laying groundwork for new deployments of the model, and fruitful application of the simulation capabilities. The scenario design, development of BEAM CORE ACT, and framework for deep dive analyses have established strong foundations for disseminating meaningful insights from BEAM CORE analyses.

I.1.4 Metrics for Assessing the Impacts of Energy-Efficient Mobility Systems (NREL; LBNL)

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Start Date: October 1, 2020 End Date: September 30, 2023
Project Funding: $1,850,000 DOE share: $1,850,000 Non-DOE share: $0

Project Introduction

As a part of SMART 1.0, the MEP metric methodology was solidified into a tool that has been applied to compute MEP scores for a little more than a hundred cities across the United States. Simultaneously, the metric has been integrated with the SMART Mobility Workflow modeling process, where outputs from land use, transportation, and energy simulation models served as inputs to calculate the MEP metric for various future scenarios associated with automated, electrified, and shared mobility. While the development of the MEP metric served the need of assessing various SMART Workflow scenario runs in SMART 1.0, some gaps 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 methodological enhancements that were discussed during 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 interaction platform
4. Collaborating with State 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 efforts proposed will directly benefit the SMART Workflow modeling process in the form of an enhanced MEP metric that can comprehensively quantify the impacts of energy efficient mobility systems. 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. Even with its relatively short development span over the last couple of years, MEP provided the best metric for assessing EEMS project outcomes. The 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 vehicle technology investments to holistic mobility and energy outcomes under these scenarios. Key objectives 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, resolving the 'red-car – green-car conundrum').
- Explore accommodation of additional weighting factors such as emissions, infrastructure quality, and safety (alongside existing, time, energy, and cost parameters) in MEP computation. The target is to include emissions at a minimum along with a review of additional factors.
- Extend the existing methodology to 1) incorporate parking wait times into the driving mode (at the link level); and 2) 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 (Behavior, Energy, Autonomy, Mobility Comprehensive Regional Evaluator) agent-based model (ABM) 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 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 (DelDOT) and Colorado Department of Transportation (CDOT) to integrate MEP calculations into travel demand models developed by respective DOTs.

Approach

Task 1

Travel Time Coefficient Updates: The travel time coefficients used in MEP calculation have been updated using data from the National Household Travel Survey (NHTS). A distinct coefficient was derived for each activity type and travel mode combination used in MEP calculation. Building on existing MEP methodology [1], a negative exponential distribution was fit to travel time distribution pertaining to each activity-type and travel mode combination (as used in [2], and [3]).

$$f(t;\beta) = \beta e^{-\beta t}, t \geq 0$$

Where,
t – travel time in minutes
β – travel time decay coefficient

Similar exercise is being carried out to estimate coefficients for energy and cost parameters.

Incorporating multimodal trips and mode usage considerations in MEP calculation: The MEP metric currently computes travel sheds or isochrones (i.e., area reachable within a given amount of travel time) for walk, bike, transit, and car modes independently. To capture the modal combinations made possible by emerging mobility options (such as walk ➔ transit ➔ ridehail), this task aims at enhancing the MEP calculation by accounting for multimodal trips. To compute multimodal isochrones, the current isochrone generation process needs to be modified to check every mode (i.e., start/end of a road link) for an inter-modal facility such as a pedestrian walkway, bus station, micro-mobility station (such as e-bikes). This increases the number of queries for each intersection by a factor of the number of alternative modes (or, in the case of transit, alternative schedules), which comes with a heavy computational cost. The MEP team is leveraging recent research in parallel computing to implement distributed search frameworks (through Apache Spark GraphX) to help reduce the computational burden and develop a computationally efficient method to generate multimodal isochrones.

Task 2

Disaggregation of existing MEP metric to reflect socio-demographic characteristics: The MEP metric was originally developed as a place-based metric [1], which is extremely useful both for baselining the effectiveness of mobility options in a location, and for understanding the impacts of infrastructural improvements in a city or metropolitan region. However, an average MEP score for a location (encompassing all modes, activities, and travel times) might not resonate with specific socio-demographic cohorts. For example, individuals who are car-constrained (age < 16, or income < 25K) might have different travel, and activity preferences compared to the average traveler. Similarly, modal and activity engagement preferences of the micro-mobility constrained, or averse (age >85) cohort might vary significantly from the average traveler. This subtask aims at addressing the need for MEP scores to be reflective of travel characteristics of specific socio-demographic cohorts. This analysis is a first step in developing the capability to view MEP results from an equity-based lens.

Individual Experienced Utility-Based Synthesis (INEXUS): In this subtask, the project team aims to develop an individual-level metric, designed to complement location-based metrics, that captures both realized accessibility and the potential for alternatives not selected. To accomplish this goal, the team assessed alternative approaches based on five criteria (feasibility, interpretability, consistency with other metrics, internal consistency within the simulation, and equitable treatment of different classes of agents in the simulation) and defined three INEXUS metrics. Using the mode choice model in ActivitySim, which is tightly integrated with BEAM in BEAM CORE, the observable deterministic portion of utility (V_{nk}) will be used for calculating INEXUS. Each of the following specifications can be estimated at the individual trip level, where the INEXUS captures the modal attributes of each available mode and destination conditional on a given trip purpose.

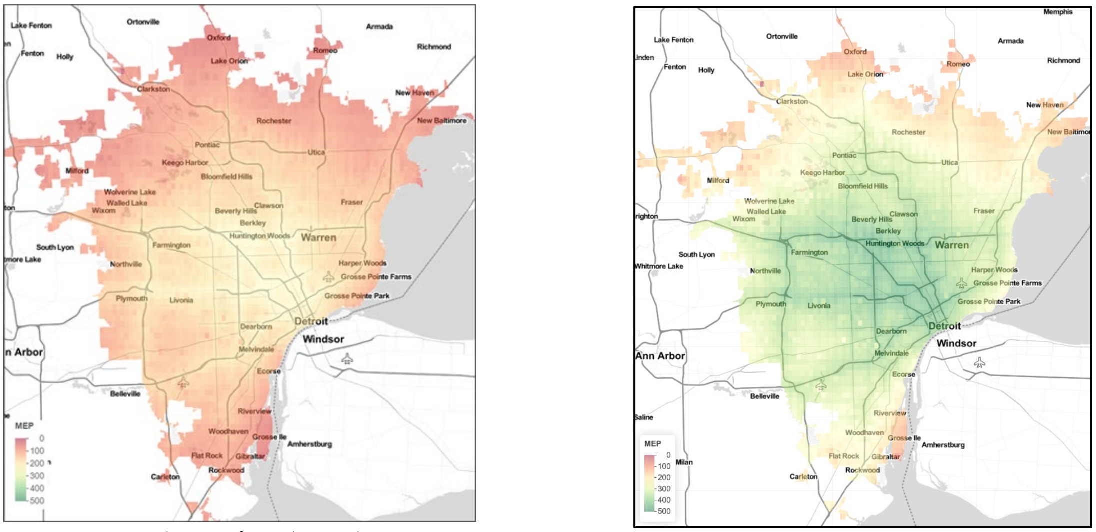
The Potential INEXUS: for agent i for trip n with transportation mode choice set TC_{in} captures the full utility of modal options, k, available to the agent for the given trip and is specified as: $P_{in} = \ln(\sum_{\forall k \in TC_{in}} e^{V_{ink}})$.

The Realized INEXUS: measures the utility experienced by agent i during trip n with mode choice set TC_{in} for the mode selected k^*, R_{ni}, and is specified as: $R_{in} = \ln(\sum_{\forall k=k^*} e^{V_{ink^*}}) = V_{ink^*}$.

The Social INEXUS: for agent i during trip n on mode selected k^*, S_{in} measures the utility experienced by and the externalities, E_{ink^*}, associated with the agent for the mode chosen and is specified as: $S_{in} = \ln(\sum_{\forall k=k^*} e^{(V_{ink^*}+E_{ink^*})}) = V_{ink^*} + E_{ink^*}$.

Results

Travel Time Coefficient Updates: The figure below shows the MEP score for driving before and after updating the travel time coefficient. Travel time decay coefficient for drive mode was updated from 0.08 to ~0.04, leading to a doubling of MEP score for the mode.



a) Before (160.5)

b) After (342.2)

Figure I.1.4.1 Drive MEP (a) before and (b) after updating the travel time decay coefficient

Incorporating multimodal trips and mode usage considerations in MEP calculation: Figure I.1.4.2 shows sample results from the multimodal search technique. The search algorithm was run using data from the Smart 1.0 BEAM San Francisco 2010 Baseline scenario [4], which provided the road network, travel times, and parking and ridehail wait times. The drive and ridehail mode travel times were increased from the original dataset by 3x to demonstrate more realistic isochrones. This search is limited by parking delays in both the departure and the arrival of the search. This search is extended with an additional 15-minute transit trip, as shown in Figure I.1.4.2 (b).

Drive Reachability

Drive+Transit Reachability

Figure I.1.4.2. Drive and *'drive+transit' searches*

Disaggregation of existing MEP metric to reflect socio-demographic characteristics: The disaggregation of the MEP scores for socio-demographic groups involves the customization of a variety of parameters used in MEP calculation. These include types of trips and their frequency, travel time tolerances, and modal preferences (or availability). An age-based analysis was carried out for Young (or non-driving) age (≤ 15 years), Driving age (16-80 years), and Old age (>80 years) cohorts. Based on the 2017 NHTS data (for the whole country), activity engagement frequencies, mode shares, and the 85th percentile travel times for different modes were obtained for each cohort, as well as the baseline (i.e., average traveler). Figure I.1.4.3 shows the location-wise school/daycare/religious MEP maps for various cohorts. National-level NHTS data shows that 42% of all trips made by the young cohort are for school/daycare/religious activity purpose. The high activity engagement frequency for this purpose for the young cohort is leading to a higher school/daycare/religious city-level MEP score for this cohort (Figure I.1.4.3 (c)) compared to the other age-based cohorts, in spite of this cohort having the second highest (but not the highest) representation relative to the total population.

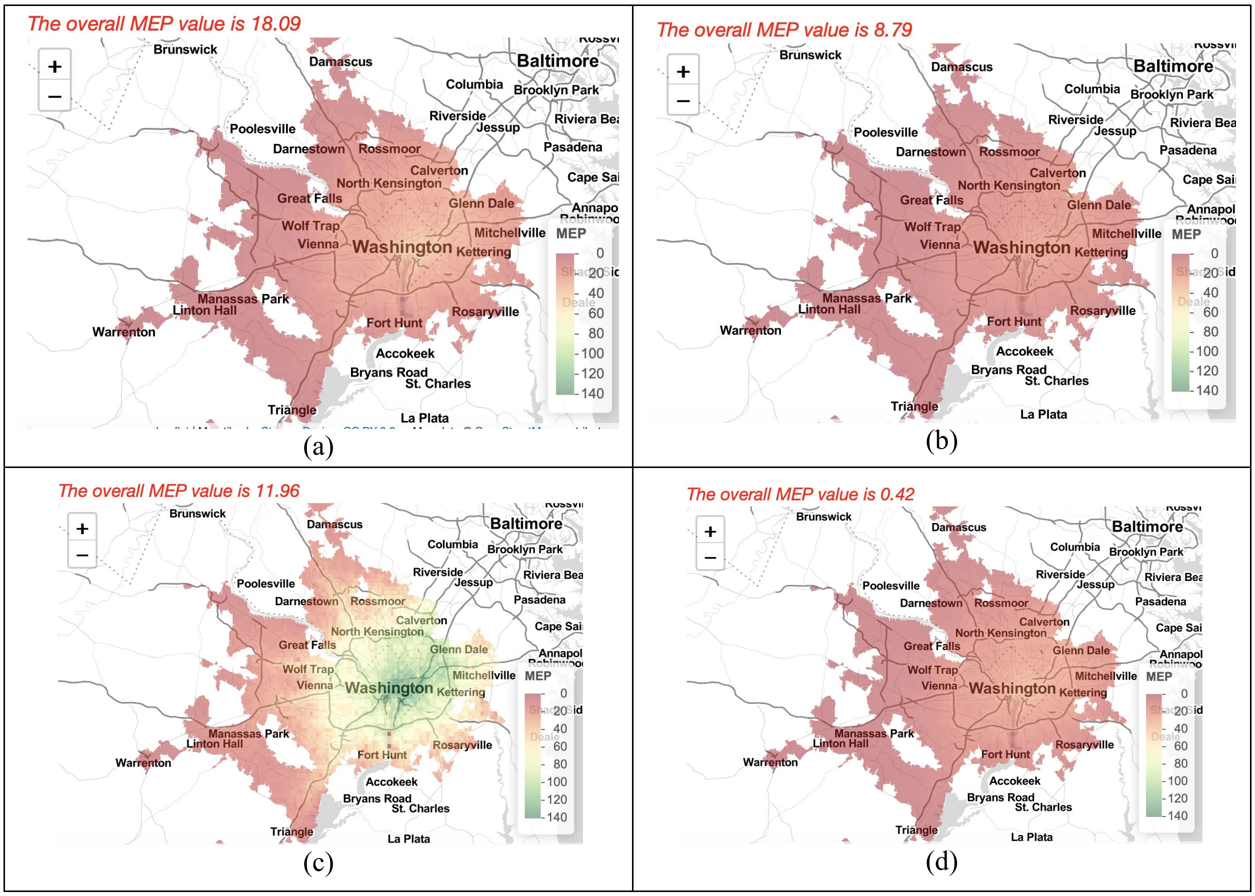


Figure I.1.4.3. Washington DC maps color coded on the basis of location-wise school/daycare/religious MEP scores for (a) the baseline cohort, (b) the driving-age cohort, (c), the young cohort and (d) the old cohort.

Conclusions

In the first year of this project, the team has made significant progress on each of the tasks by: 1) deriving travel time, energy, and cost coefficients for specific mode and activity type combinations, 2) developing multimodal routing capabilities, 3) extending the MEP methodology to accommodate variations in travel preferences of various socio-demographic segments, and 4) finalizing the formulation for an individual-level version of the MEP metric. Next year's efforts will focus on implementing all these changes in the MEP calculation procedure. Parallel efforts are underway to enhance the computational efficiency of MEP code. These changes along with enhanced run times, will facilitate MEP calculations for a wide range of scenarios to be run in the SMART workflow in FY22 and FY23.

Key Publications

1. Chris H, Ambarish Nag, Venu Garikapati, and Stan Young. Evaluating equitable mobility impacts with the Mobility Energy Productivity Metric. Abstract submitted for presentation at the Sustainability and

Emerging Transportation Technology (SETT) conference to be held from March 15–18, 2022 in Irvine, CA.

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From the project team: The project team would like to extend their sincere thanks to the DOE leadership (David Anderson; Michael Berube), and EEMS technology manager Heather Croteau for their regular feedback on the development of this metric.

I.1.5 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 (MaaS) and other shared mobility options and builds on findings from a 2019 Vehicle Technology Analysis Program (VTAP) 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 will be 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 Mobility-Energy Productivity (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

Objectives of this project are to establish fundamental micromobility research to inform efforts within Energy Efficient Mobility Systems (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. These include:

(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: Initial results include energy estimates of micromobility detailed in an energy bounding analysis paper, titled, "Estimating energy bounds for adoption of shared micromobility" published in Transportation Research Part D (https://www.sciencedirect.com/science/article/pii/S1361920921003102). Key findings are:

- Shared micromobility can reduce energy consumption of passenger travel by 2.6%.
- Micromobility induced transit trips offer highest energy saving potential.
- Micromobility energy impacts are tradeoff between energy intensity & service range.
- Sensitivity Analysis shows distance threshold has strong influence on energy impact.

Figure I.1.5.1 Sensitivity analysis of energy benefit with respect to redistribution energy intensity and distance threshold at the national level. Note: M-bike = manual bike; E-bike = electric bike; E-scooter = electric scooter; DT = distance threshold change; and RD = redistribution energy intensity change.

The team continues to discuss with the BEAM team regarding incorporation of insights from the micromobility mode share model in BEAM.

Task 2: LBNL finished analyzing docked bikeshare data in eight cities to date. All the docked bikeshare programs include persistent bike identification, which allows estimation of the fraction of all trips and all VMT that are repositions. Table I.1.5.1 compares summary statistics from programs in these cities to the five cities analyzed previously. Fraction of trips and VMT that are repositions tend to be lower, and average distance of rides and repositions tend to be higher, in these three cities than in all other cities (other than New York).

Table I.1.5.1 Summary of Individual Docked Bikeshare Ride Data from Five Cities

City	Percent trip/VMT repositions		Average distance (miles)*		Average ride duration (mins)*	Average ride speed (miles/ hour) *†	Percent rides >5 hours	Average monthly rides per bike	
	Trips	VMT	Rides	Repos				2018	2019
NYC CitiBike	2.4%	4.4%	1.16	2.16	15	4.6	0.1%	26	24
SF Bay Wheels	9%	13%	1.04	1.53	13	4.9	0.2%	47	45
Jersey City CitiBike	10%	14%	0.63	0.90	12	3.2	0.2%	12	14
Detroit MoGo	11%	17%	0.74	1.26	24	1.9	0.5%	0.8	0.6
Austin MetroBike	13%	16%	1.02	1.33	23	2.7	0.9%	70	18
Chicago Divvy	7%	10%	1.32	2.02	18	4.5	0.2%	12	13
DC Capital Bikeshare	7%	12%	1.11	2.02	17	4.0	0.2%	14	12
Boston Bluebike	6%	9%	1.23	1.75	18	4.2	0.3%	14	14

*Eliminates rides over 5 hours

†Calculates MPH by dividing average distance by average duration

The augmentation of dockless bikesharing data with distance and elevation data was completed for much of the datasets available. This added elevation profile information to the data containing origins and destinations of micromobility trips. The analysis has also begun mapping state of charge (SOC) by trip and other attributes of activity to understand better where micromobility modes may consume the most energy.

Under a project funded by the U.S. EPA, LBNL will be simulating several scenarios regarding micromobility to transit in the San Francisco Bay Area. Validation of baseline conditions using individual micromobility trip and repositioning data continues. Once complete, micromobility to transit scenarios will be run.

Task 3: The research team analyzed micromobility data shared by DCDOT in two datasets that covers a time span between Sept 2017 and Dec 2018, to align with non-micromobility data for the same region to inform behavioral model development. A preliminary data analysis was conducted to enable an initial understanding of DC micromobility usage data. After initial data filtering, the travel time and travel distance distribution of remaining trips are shown below in Figure I.1.5.2. It should be noted that DC micromobility data does not have actual travel distance information, instead the distance was derived from the latitudes and longitudes of origins and destinations. The travel time distribution and travel distance distribution are like micromobility data in other cities the research team examined before.

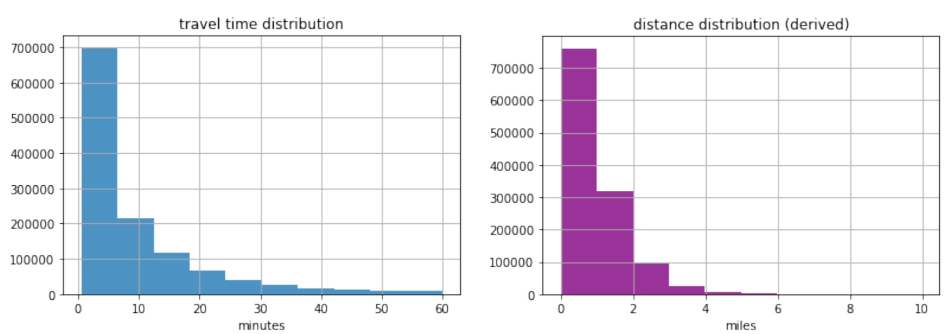

Figure I.1.5.2 DC Micromobility Travel Distance and Travel Time Distribution

Among three vehicle types, manual bikes, e-bikes, and e-scooters), e-scooter have comparable percentages in terms of fleet size and trips served, however, manual bikes and e-bikes are quite different. E-bikes served relatively more trips than manual bikes, when fleet sizes are compared, suggesting e-bikes are preferred over manual bikes by micromobility users.

Task 4: The MITIE team continues to engage with stakeholders, including system operators and micromobility managers in cities to inform parameters for scenario development. The team engaged with the North American Bikeshare and Scootershare Association (NABSA), resulting in emerging plans to secure data from participating micromobility systems, and to further engage with those systems to better understand how research outcomes could support their operations. Of particular interest for NABSA are tools and information to assist cities and municipalities in determining optimal system size and operations, based on various parameters. They noted that readily accessible and no-cost resources to assist planners, particularly in midsize and smaller cities, could greatly increase the number of communities to offer shared micromobility options. This kind of assistive or informational tool does not presently exist for informing interested communities to plan for micromobility implementation. Informed by the present work, under this scheme input variables, such as location and population size, augmented by additional factors, such as demographic and climate characteristics, geography, and urban density, could quickly return a target range of micromobility system parameters.

The MITIE team continues to be contacted by or identify collaborative opportunities with other micromobility studies and operations. An e-bike program in Massachusetts was informed by the Colorado Energy Office's 'Can Do Colorado eBike program' and is evaluating proposals for the program. The Massachusetts Clean Energy Center (MassCEC) has been in contact with the MITIE team and is interested in using OpenPATH in their program for data collection and would serve as a data source similarly to the Colorado program.

Task 4A: ANL developed an e-scooter data acquisition (DAQ) system for data collection from on-road operation. An e-scooter, complete with the Raspberry Pi based DAQ system, is shown in Figure I.1.5.3.

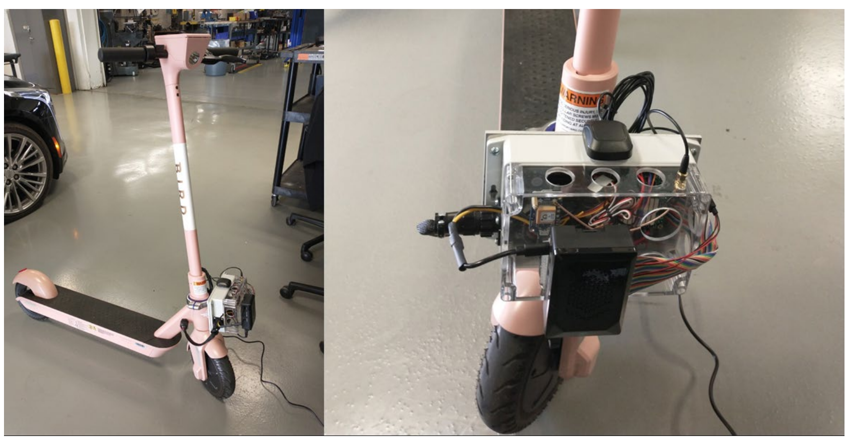

Figure I.1.5.3 Bird One e-scooter with Raspberry Pi based data acquisition system

Calibration of the accelerometer sensor included collecting data with the scooter in various static positions. This was used to determine the orientation of the accelerometer sensor, as mounted, relative to the scooter. With the exact sensor orientation known, the raw accelerometer sensor data can be converted into accelerations relative to the scooter reference frame. Finally, this gives the ability to use accelerometer data to estimate the scooter's velocity and depending on the noise and accuracy of the data, road grade information. The scooter's reference frame is defined with the x-axis going through the center of the two wheels and positive from the rear to the front. The y-axis is positive to the right, and the z-axis is down.

Data collection for on-road scooter operation included multiple rides along ANL campus roads, multiple riders, and focused on-road testing with a specially designed test plan. The data from normal riding on ANL campus roads provides a good average energy consumption as a function of distance, in terms of energy use per mile travelled [Wh/mi].

Task 5: A literature review conference paper was written to assess the state of micro-freight research and industry deployment as well as related policies. It was presented on August 9th at the 2021 World Symposium on Transport and Land Use Research conference in their 'Freight Issues' category. Additionally, a meeting with Freight Mobility staff at NYC DOT at the beginning of the quarter offered insight into the city's Commercial Cargo Bicycle Pilot Program. City staff had questions and concerns about how cargo bike data, if shared or solicited from their private sector partners, would ultimately be used and beneficial for them. These are questions we are working to answer and follow up on. We have also connected with staff at the University of Washington's Urban Freight Lab, which fosters public private partnerships for urban freight innovation, including microfreight pilots. Data needs for energy analysis have been identified and are being relayed to industry contacts in search of partners for field-based data collection. Field-based data will also allow geospatial and behavioral analysis.

Conclusions

The MITIE team has made substantial progress during the past year and is on the anticipated timeline. Some disruption to initial plans was encountered due to the COVID-19 pandemic, but the team adapted to changing contacts and operational environments. As a central goal and Go/No-Go decision point, an initial set of micromobility scenarios to inform the Workflow models was delivered in Q4, having been informed by project task work and co-developed for the needs of Workflow teams. This initial micromobility scenarios set identifies core, conservative, and aggressive scenarios for each of three key levers: 1.) Market penetration of micromobility (behavioral adoption rates of micromobility; 2.) Micromobility mode preference (rates at which micromobility modes are selected to replace other modes); and 3.) Shared micromobility fleet management (operational parameters of micromobility systems, large maintenance vehicle types and quantities for collecting micromobility vehicles for repositioning, charging). Initial findings suggest that micromobility operations 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. The project continues to advance and adapt as new micromobility data and implementations emerge.

Key Publications

1. 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)

2. 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, Leidy Boyce, Chad Hunter
- LBNL: Tom Wenzel (Co-PI), Elliot Martin, Zach Needell, Michael Mills, Xuan Jiang
- ANL: Simeon Iliev (Co-PI)
- DOE: Jake Ward, David Anderson

I.1.6 Dynamic Curbs: A Data-driven Simulation Tool for Dynamic Curb Planning and Management

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Project Introduction

The rapid growth of new mobility services (e.g., ride-hailing, car-sharing, on-demand delivery, and micromobility) 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 (ITF) [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, vehicle-miles traveled (VMT), energy use, and greenhouse gas (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 collaborating with the University of Washington's (UW) Urban Freight Lab, Lawrence Berkeley National Laboratory's (LBNL) Behavior, Energy, Autonomy and Mobility (BEAM) development team model development team, National Renewable Energy Laboratory's team from the SMART 1.0 curb metrics project, and Lacuna, a smart cities technology company supporting the open-source Mobility Data Specification for municipal sensor platforms.

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 controlling price, number of spaces, allowed parking duration, time of sale or 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: PNNL and UW are developing enhancements for Planung Transport Verkehr's (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, and Lacuna are collaborating on the development of the curb allocation controller via online, stochastic optimization utilizing objectives (occupancy, VMT, emissions) and control variables (price, supply, maximum parking time) determined by stakeholder engagement. This control is then evaluated in the microscale curb simulation environment to determine control policy effects on traffic flow.

3. Data collection, and microscale ground truth validation: UW and Lacuna will provide existing curb management pilot data for the purpose of ground truth validation in collaboration with PNNL 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 and UW will extend a previously developed commercial loading zone communications application funded by VTO to integrate zoning control policies tested in the microsimulation environment with a communications functionality for the purposes of technology demonstration.

5. Stakeholder engagement and technical demonstrations: Through the formation of working groups (e.g., Seattle and Bellevue, WA), 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.

Results

The project has completed necessary functionality improvements and custom code integration to simulate parking behaviors in Vissim. Figure I.1.6.1 illustrates a snapshot of a Vissim simulation with curb interactions modeled on a street in downtown Seattle. This simulation capability has been used to measure speed-flow relationships as part of a contextual fundamental diagram. Figure I.1.6.2 illustrates speed flow data generated by Vissim in the above scenario, with canonical concave polynomial speed-flow relationship fits, in addition to

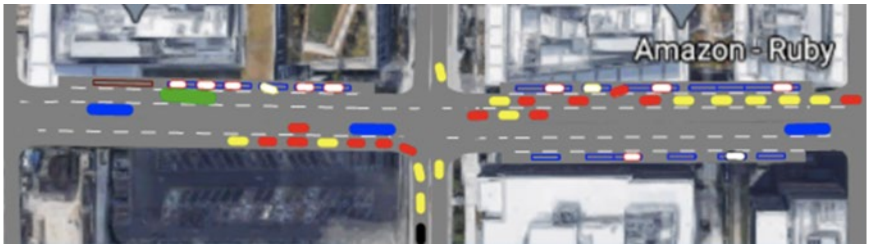

Figure I.1.6.1 Snapshot of Vissim simulation of curb activity modeled on a street in downtown Seattle

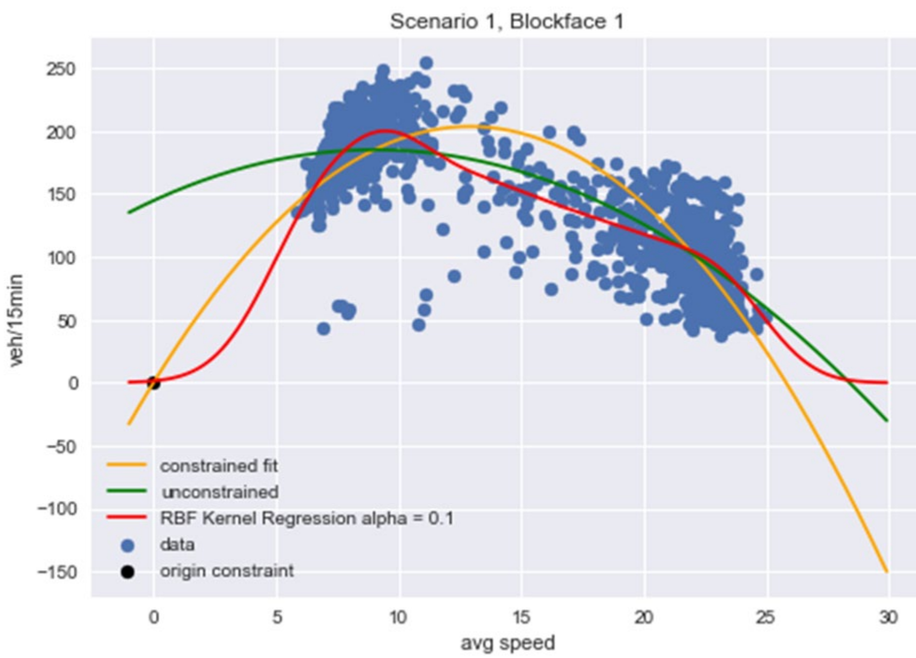

Figure I.1.6.2: Contextual fundamental diagrams measure speed-flow relationships regressed on VISSIM simulated data from the above prototype scenario.

a more sensitive kernel regression fit that characterizes non-idealized flow realized on a street with curb interactions and impediments to traffic flow. This diagram is a prototype of the type of information that will be integrated into BEAM for various curb configurations. These diagrams are an important improvement on the state of the art: fundamental diagrams are typically used to measure the relationship between travel speed, vehicle volume, and density on an idealized roadway like a freeway. We are extending this concept to richer, urban environments where exogenous independent factors, especially curb zoning configuration, impact the flow of traffic due to issues of compliance (double parking, lane blocking), curb use (busses pulling in and out), and competition for space (cruising for parking). This is particularly useful to EEMS, as the DoE can use fundamental diagrams to understand energy expenditure profiles for varying types of transportation land use and design. More refined understanding traffic flow has also lent itself to applications for connected vehicle interactions on highways [7], which we are investigating the connection to urban streets and learning these contextual fundamental diagrams.

Figure I.1.6.3: Current real curb zoning in a portion of downtown Seattle (left) and curb zoning reallocated according to NREL SMART 1.0 curb metrics combined with available historical and sensor data.

A controller has been designed, with curb valuation functions developed based on NREL's SMART 1.0 curb metrics project. Figure I.1.6.3 illustrates a current, real zoning configuration in downtown Seattle, compared to a reallocated zoning based on available data and the resulting valuation of curb real estate according to these metrics (i.e., moving commercial loading closer to building entrances at the center of city blocks).

To compute these rezoned allocations dynamically over time, we have used historical curb demand data to test the effectiveness of an approximate dynamic programming approach. While dynamic zoning can be solved as a convex mixed integer program, the complexity of the problem increases exponential in number of spaces and length of time horizon considered. Thus, we develop an approximate dynamic programming solution.

Conclusions

The project's first year has laid the groundwork for completing the systems integration with micro and mesoscale simulators, in addition to deploying these tools into a communications platform for technology demonstration purposes. Additionally, the computation of contextual fundamental diagrams of traffic flow represents a significant advance in the state of the art in transportation engineering and traffic flow analysis. We are preparing our first round of major publications after giving several successful conference talks on our preliminary findings.

Key Publications

Accepted conference presentations and seminars on preliminary findings and results:

1. UW Data Science Seminar, March 2021**, "Fusing Confusing Data Streams: Insight into Seattle's Transportation System"**

2. INFORMS, October 2021, "Analyzing Traffic Impacts of Different Curbspace Management Strategies through Simulation"

3. INFORMS, October 2021, "Optimal Dynamic Curbside Zoning"

4. TRB, January 2022 (to appear), "Turning Curb Metrics into Curb Policy"

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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1. University of Washington Urban Freight Lab: Dr. Andisheh Ranjbari

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

3. Lacuna Technologies: Dr. Stephen Zoepf

4. National Renewable Energy Laboratory: Dr. Alejandro Henao

I.1.7 SMART 2.0 Workflow Improvements & Automation (ANL)

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Project Introduction

The Argonne-led SMART Mobility modeling workflow has been developed to evaluate new transportation technologies such as connectivity, automation, sharing, and electrification through multi-level systems analysis that captures the dynamic interactions between technologies. Through integration of multiple models across different levels of fidelity and scale (i.e., individual vehicles to entire metropolitan areas), the workflow has been designed to yield insights about the influence of new mobility and vehicle technologies at the system level. The Argonne-led workflow has generated significant insights in SMART 1.0, ranging from vehicle and powertrain control energy saving potential, impact on mobility and energy of shared vs privately owned driverless vehicles, to e-commerce and overall freight impact. The results highlighted the need to consider a much larger number of scenarios to, for example, characterize the impact of individual technologies (e.g., ride-hailing, e-commerce) or the need to consider uncertainties has become apparent.

Several barriers have prevented existing mobility and energy simulation tools from being used to explore many scenarios, including:

- Numerous manual steps, which required coordination amongst staff from multiple National Laboratories to manually launch their processes and transfer data back and forth.
- Lack of robust user interfaces for efficient simulation setup and analysis.
- Ad-hoc, file-based connections between many tools.
- Computational barriers and inefficiencies in many tools.
- Lack of post-processing tools to analyze results and perform quality checks quickly and consistently.
- Limited validation, calibration of stand-alone tools and no calibration for joint process.

Objectives

This project focuses on addressing each of the identified individual barriers to large scale deployment identified in the SMART1.0 project. This will be achieved through:

- Enhancing and automating the Argonne-led SMART workflow to enable the simulation of a very large number of scenarios efficiently.

- Increasing computational efficiency using both HPC and cloud computing to decrease overall workflow run-times.
- Deploying the workflow and its results to multiple stakeholders, including users and developers, using professional user interfaces.
- Analyzing and visualizing results from individual and multiple runs.
- Validating individual models along with verifying the performance of the full toolchain for specific technologies to enhance end-user confidence in model predictions.

The project will lead to the successful deployment of the SMART workflow at scale on multiple platforms to support scenario analysis for an increasing and diverse set of stakeholders. The successful improvement, automation, and deployment of the workflow.

Approach

The approach taken to meet the project objectives involves five primary subtasks, shown in Figure I.1.7.1, along with a separate ongoing subtask dedicated to workflow verification and validation.

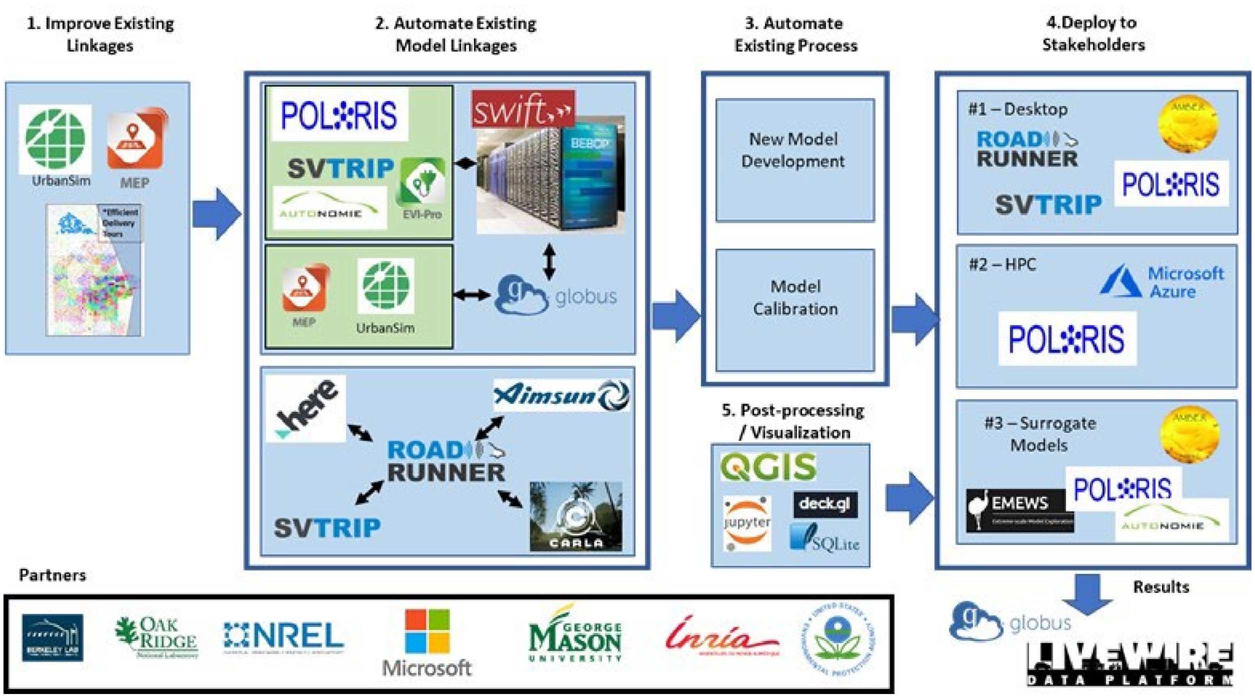

Figure I.1.7.1 Workflow Improvement and Deployment Process

Workflow refinement and deployment tasks include:

- **Subtask 1 – Refine existing workflow tools and linkages**: This task is focused on refining the existing workflow by improving connections between POLARIS, UrbanSim, MEP, and truck tour formation models and by improving computational efficiency of the MEP and truck touring model.
- **Subtask 2 – Automate workflow connections**: This task involves transitioning all workflow components to run in HPC or cloud environments, automating connections and run routines between each tool through script development, and automating linkages between RoadRunner and Microsimulation, as well as integrating traffic into RoadRunner. Additionally, this subtask includes ongoing work to incorporate new modeling features into the existing workflow as they are developed.

- **Subtask 3** – **Automate Model Development and Calibration**: In this task, automated routines for component model calibration will be improved and extended to freight parameters, and a new RoadRunner production control calibration methodology will be developed.
- **Subtask 4 – Deploy Workflow and Surrogate Models**: This task involves deploying the workflow in a variety of platforms including in AMBER, Azure Cloud, and as stand-alone surrogate models for quick response.
- **Subtask 5 – Improve Postprocessing and Visualization:** This task is focused on developing capabilities to properly analyze and visualize model results from large multi-scenario studies using a variety of tools, to quickly and meaningfully convey model results to end users.

Finally, along with the refinement and deployment of the workflow, there will be an ongoing validation and verification task—**Subtask 6**—demonstrating the performance of the full toolchain for a variety of technologies. Together, the completion of these subtasks will result in a workflow with expanded modeling capabilities that can be quickly deployed to new contexts through calibration and used in an automated manner to run and analyze large-scale studies efficiently, through a variety of platforms.

Results

Subtask 1 – Refinement of Workflow Components

Over the previous year, several of the component tools in the SMART Mobility workflow were improved and connections to the other workflow tools were strengthened. First, the MEP metric calculation was improved for computational efficiency and to allow automated calling. The MEP Metric evaluates the ability to reach different activities in a region using a variety of travel modes. The MEP calculation happens on metropolitan-scale data sets with hundreds of thousands of rows of data. It is a compute-intensive process due to the need to perform many path searches for a single regional MEP. This was previously executed using R, a scripting language, sending many queries to a PostGres database which would perform the path search, and finally processing the result in R. The entire process has been rewritten to run as an application on Amazon Web Services (AWS), using AWS Lambda and Elastic Map Reduce (EMR), and written using the Apache Spark framework for distributed analytics. Initial experiments have shown a 50% speedup (~ 2-hour runtime), reducing costs related to compute infrastructure. MEP calculation gained efficiencies in routing queries (for isochrone generation), and spatial intersection of land use data and isochrones, along with speed-ups in the base scientific computation. Additionally, the connection between the UrbanSim land-use forecasting tool and POLARIS was strengthened through enhanced data exchange mechanisms and automated calling. The UrbanSim model was deployed using a Docker container and made available to run on Argonne HPC resources, and a run script called PILATES was developed by LBNL and adapted by Argonne to initiate integrated model runs. Finally, an open-source heuristic that replicated the ORNL freight tour modeling process was developed and implemented in Python. An I/O process to integrate the Python tool with POLARIS was also developed and tested within the workflow.

Subtask 2 - Automation

POLARIS was migrated to Linux and re-written to be compatible with GCC8.4 and 9.3 compilers, which enables cross platform compilation. The software can now be executed in an Argonne HPC environment, currently the Bebop cluster. The POLARIS code is now running approximately 2.5 time faster than previous, after shifting to Linux-based platforms and improving code optimization and memory management improvements. There is also ongoing exploration to identifying how to integrate the other tools in the SMART Workflow tools chain. SvTrip is currently being migrated so that it can be executed in an Argonne HPC environment. Python was used to define workflows where external tools (like UrbanSim) are executed using containers in the same environment as POLARIS. Preprocessors and postprocessors are called to convert data into formats each tool can use. The python code determines the flow of data and when the pre/post processors are required. This enables the UrbanSim component, distributed and containerized in Docker, to be run in the

Argonne HPC environment as well. Python was also used to develop a workflow where POLARIS is executed in an HPC environment, and the results are moved to an AWS environment. Then, a signal is sent to the MEP process to execute. This methodology allows the scheduling of multiple workflows in parallel.

To better model driving in traffic situations prototype process for linking SUMO (traffic flow simulator) and RoadRunner was developed. The linkage consists of synchronizing the road attributes between the two tools, and “replaying” some of the traffic situations from SUMO within RoadRunner. The workflow is shown in Figure I.1.7.2. First, in SUMO, a real-world network is generated, and on that network, one vehicle is selected as “ego-vehicle”—vehicle of interest. The attributes for the route followed by the vehicle are extracted: segment length, speed limits, traffic light phase and timing (SPaT), etc. In RoadRunner a “mirror” scenario is generated, and a dummy preceding vehicle (PV) follows the recorded trajectory of any PV that appeared in front of our ego vehicle in SUMO from SUMO. The ego vehicle in RoadRunner reacts to traffic rules and to the dummy PV based on its own controller. This new workflow enabled us to improve the robustness of CAV controls in traffic situations previously not modeled, such as such as queues before traffic lights and unexpected cut-ins.

Figure I.1.7.2 Workflow for linking SUMO with a RoadRunner one. Preceding vehicle trajectory and SPaT information are extracted from SUMO and used in RoadRunner

Subtask 3 - Calibration

The objective of this task is to implement auto-calibration routines for both POLARIS and vehicle control. Over the previous year, the development and implementation of the Gaussian process calibration routine (Figure I.1.7.3) initiated in SMART 1.0 with GMU for passenger travel was completed for an initial set of parameters and later expanded. The parameter sets are identified for behavior sensitivity as new features are added to the POLARIS model throughout the year such as EV charging, new modes, etc. New parameter sets are being identified and results are being analyzed to improve the process.

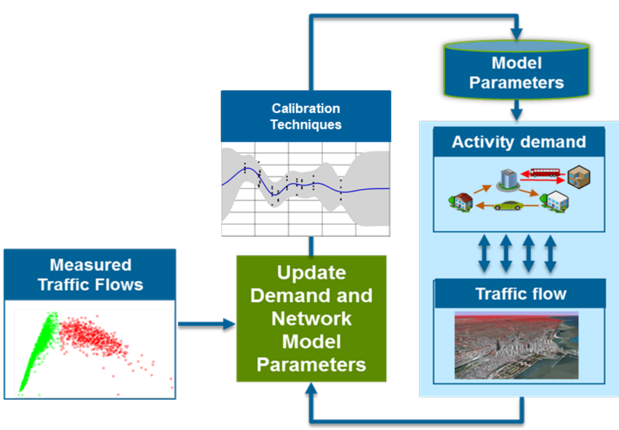

Figure I.1.7.3 Parameter calibration process

Every controller, even ones featuring optimization and intelligence, includes parameters that impact their performance—e.g., the energy saving level of eco-driving CAV controls. As a result, a first version of the automated calibration process for models and controllers developed in RoadRunner/Simulink environment was developed so that controllers can be run with their best calibrations. The process calls a global optimization routine that minimize a given cost function (e.g., a trade-off between energy consumption and travel time) by iteratively running RoadRunner simulations and updating the parameters of the models. As this process is computationally intensive RoadRunner was enabled to run simulations on a parallel computing cluster, thus making the calibration process feasible.

This process was demonstrated on a case study for 13 real-world route scenarios, optimizing 4 parameters of our “speed-only” CAV eco-driving control for a battery-electric vehicle (BEV) and internal combustion engine vehicle (ICEV). After optimization, the CAVs accelerate and brake more smoothly, maintain lower cruising speed and limit the need for braking or stopping at stopping by “catching” more green lights. Overall, this calibration added up to 8 percentage points of energy savings, while not increasing total travel time, compared to the baseline parameters (manually tuned), as shown in Figure I.1.7.4.

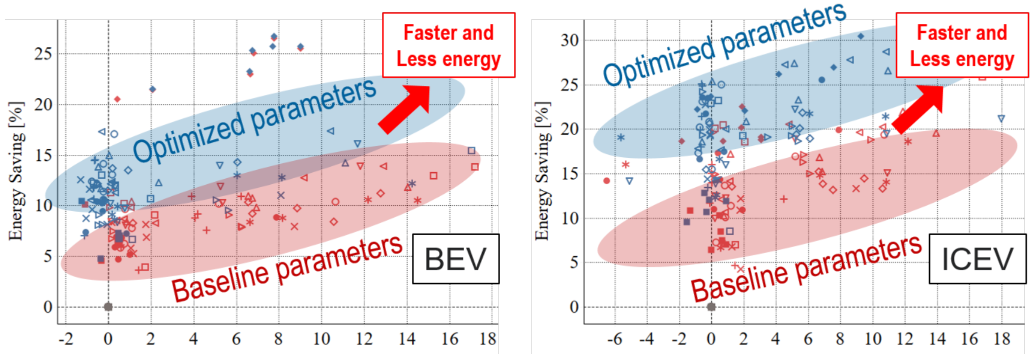

Figure I.1.7.4 Energy vs. travel time saving for CAVs with controls optimized through new calibration process and unoptimized ones, for 13 real-world urban route scenarios.

Subtask 4 - Deployment

Multiple pathways toward deployment of the POLARIS workflow were explored over the previous year, in addition to the direct deployment of the full workflow on HPC, to enhance external use of the tools. The two primary methods that were pursued include deployment in Argonne’s AMBER workflow management tool, and through Microsoft Azure cloud deployment. The deployment in the AMBER workflow manager involved developing a front-end interface to the workflow that allowed the specification of model settings, scenarios setting, and input files in an interface design using the AMBER XML process. The interface in AMBER currently supports specifying a single POLARIS run, but it will be extended in the future to specifying and launching full POLARIS workflows and other SMART Mobility workflow tools. An example of the interface can be seen in Figure I.1.7.5. Additional work in the previous year has begun to explore a shift of the POLARIS HPC process to Microsoft Azure cloud deployment.

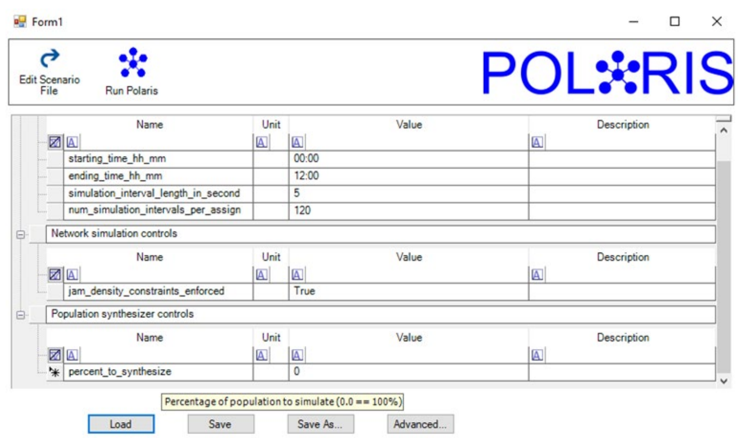

Figure I.1.7.5 AMBER POLARIS interface

In FY21, RoadRunner was further integrated within the AMBER environment, with a focus on automating the tasks required for SMART 2.0 research and developing advanced graphical user interfaces for greater usability and easier deployment. The newly developed graphical road/scenario builder graphical user interface (GUI) allows the user to load an existing route file either from a real-world map or a user defined Matlab file, or to create one. The GUI helps the user to visualize the road intersections (stop signs and traffic lights visible in Figure I.1.7.6) as well as the speed limits and the road grade all along the route. The user can also modify, add, or delete any road attribute (speed-limit, grade, stop sign or traffic light) and save the new route to be used in RoadRunner simulations.

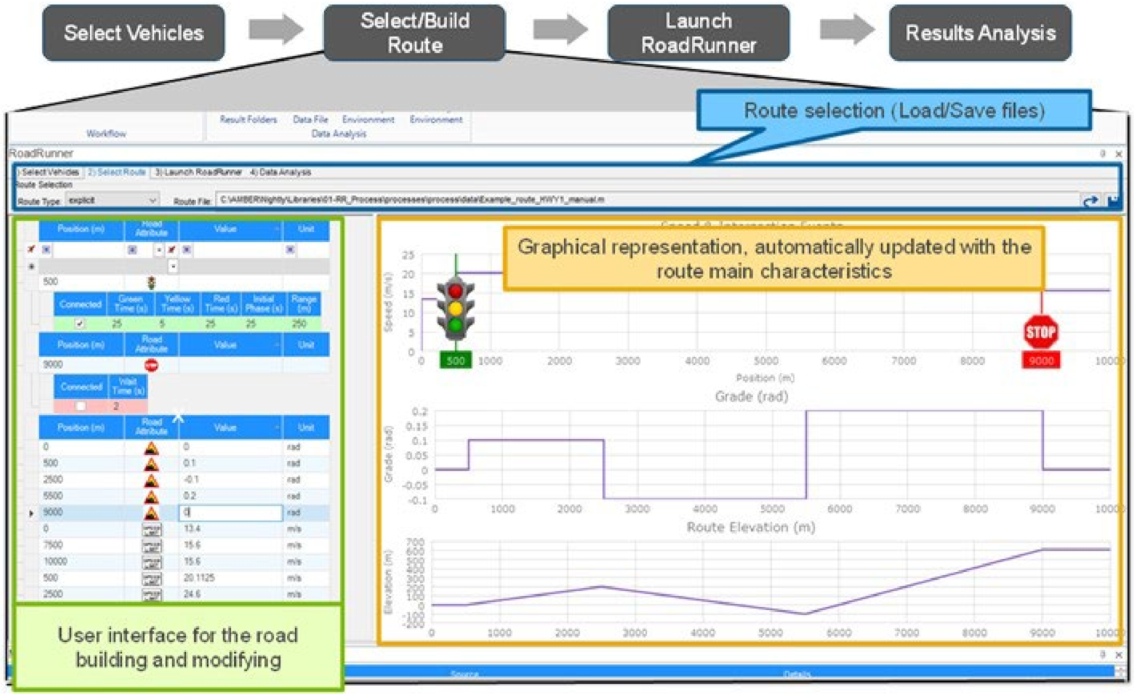

Figure I.1.7.6 Road/Scenario Builder GUI in RoadRunner

In addition, RoadRunner core code has been significantly improved by implementing AMBER's workflow management system. This enables to turn RoadRunner from internal developer-focused tools into robust, professional-looking software that can elevate the research capabilities for SMART 2.0, as well as reach a broader audience of researchers and engineers. The integration of RoadRunner into AMBER includes tight integration of the tools not only with AMBER, but also to a software lifecycle process, which covers issue management, source control, testing and release generation. Other notable new features for RoadRunner include the improvement of the main simulation workflow using API (application programming interface), making it easier for the user to parametrize the simulations, including the ability to "batch-define" parameters and scenarios, as well as the ability to run parallel simulations with MPI (message passing interface) or HPC (high-performance computing) clusters. SVTRIP, previously a Matlab command-only tool, was integrated into AMBER. A new SVTRIP workflow within AMBER enables the user to load a trip definition file in CSV format, parametrize SVTRIP algorithm and run the generation. SVTRIP was also integrated within the software life cycle process that is used for AMBER, Autonomie and other Argonne tools, making it easy to generate releases of AMBER featuring SVTRIP.

Subtask 5 - Postprocessing

As the number of scenarios considered in the workflow increase, the ability to properly analyze and visualize model results becomes more critical. Current analysis and visualization capabilities for critical components of the workflow (POLARIS, RoadRunner…) are generally manually implemented or scripted and performed for a single model run. Therefore, it was decided to use Python and Jupyter to process POLARIS results rather than existing software options (Tableau, etc.). This was done to tailor the process to our specific needs without having to work around a more generic platform. The goal was to provide graphing and mapping abilities to display POLARIS data on a map that the user can interact with, as well as provide POLARIS outputs to a graphing utility to visualize results and compare multiple model runs. The post-processing analysis that was developed can be automatically applied to a list of Demand files output by POLARIS model runs. The resulting data tables, as well as basic summary info on each run, can then be printed in graph form, with control over the specifics of how to display the data. The Jupyter tool enables coordinate data (from network supply files) created by multiple POLARIS model runs to be displayed and compared (shown in Figure I.1.7.7)

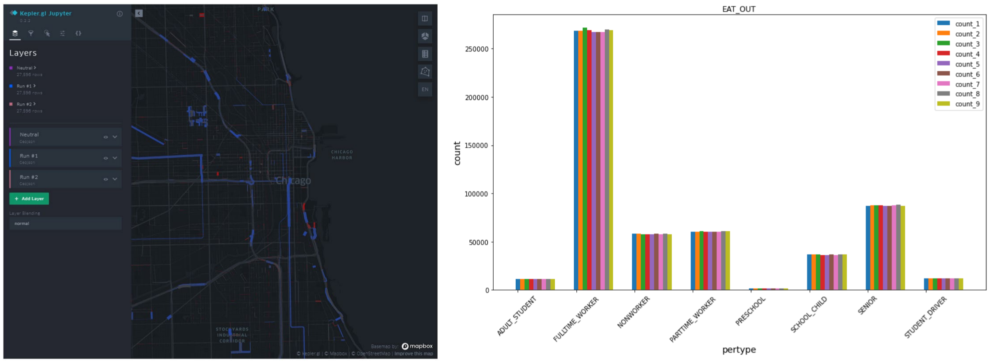

Figure I.1.7.7 Map display on left, Graphing utility on right/From Jupyter output)

Analyzing CAVs operations in RoadRunner is complicated by the fact the data becomes spatiotemporal – unlike a drive-cycle based analysis which is purely temporal. Therefore, the development of a visualization tools to effectively display spatiotemporal results was initiated. The visualizer will feature synchronized signal plotting and a 2D “top road view” animation. Prototypes for both components were developed in FY21. The signal plotter, developed in Python/Dash, allows comparison of different signals for across multiple vehicles or simulations, and can be run from AMBER. The 2D animation (Figure I.1.7.8) shows a 2D top view of vehicles moving along a road with traffic signs and is automatically generated from RoadRunner simulation results. The user can adjust replay speed as well as visualization scale.

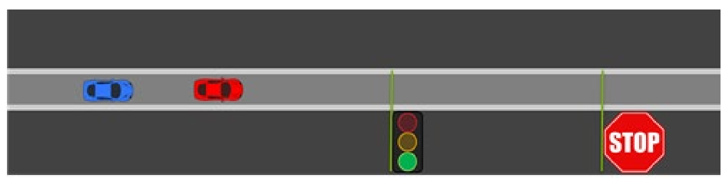

Figure I.1.7.8 Prototype of a 2D animation showing a 2D top view of vehicles moving along a road with traffic signs, based on the results of a RoadRunner simulation

Subtask 6 - Verification

The goal of this task was to quantify the impact of one of the key technologies modeled in the SMART Workflow across different tools. The technology analyzed was Cooperative Adaptive Control. In a combined effort between ANL and LBNL, a set of comparable scenarios was developed and launched in two different tool chains: Aimsun/Autonomie Express and POLARIS/SVTRIP/Autonomie. The Aimsun tool chain has a higher level of fidelity on the traffic flow simulation compared to POLARIS. On the other hand, POLARIS models demand elements that Aimsun does not. The simulations were conducted, and the results analyzed. In summary, both tools can replicate the effect of CACC. In Aimsun the benefits seem higher than in POLARIS since the benefits of CACC on flow are reduced due to induced demand. A comparison of flow results for a corridor from ach model is shown in Figure I.1.7.9

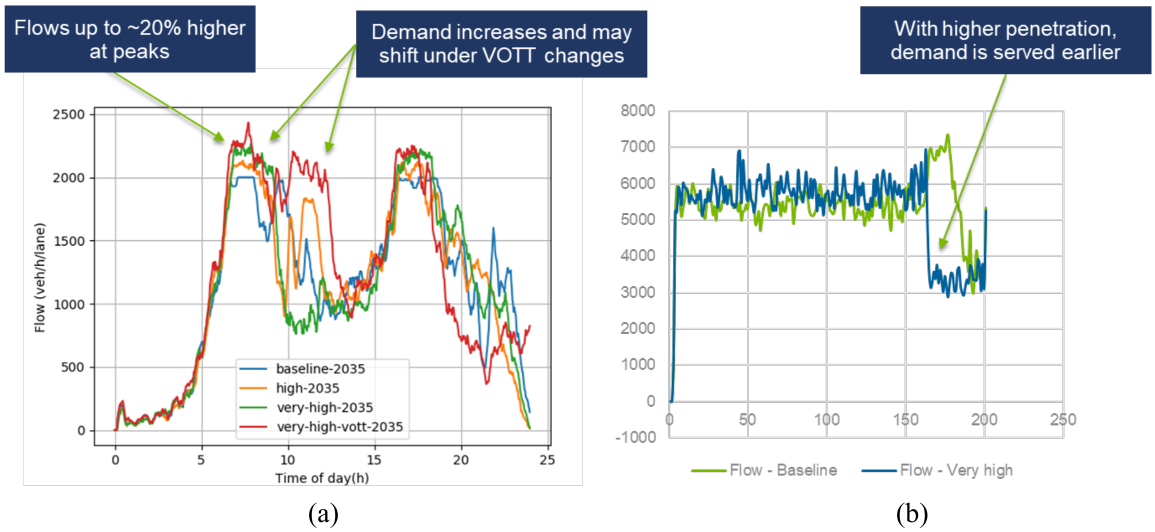

Figure I.1.7.9 Flow by time of day from corridor in (a) POLARIS and (b) AimSun

Conclusions

Over the previous year, the POLARIS-Centric SMART Mobility Workflow has been substantially refined in terms of individual tool computation, connections between tools, and tool deployment. Most of the workflow, including the most computationally intensive aspects of the workflow (POLARIS, UrbanSim), have been fully shifted and run on HPC platforms. The shift to Linux-based HPC platforms for the POLARIS code along with core modeling improvements have enabled the simulator to run approximately 2.5 times faster than on the previous Windows workstations. A process to quickly calibrate the models based on city-specific field data was also implemented. To analyze the large amount of data generated in the large studies enabled by this shift, new post-processing tools were also developed. The tools were more than adequate to replace the existing manual processes. Finally, a verification study demonstrating the ability of the toolchain (POLARIS + SVTrip + Autonomie) to replicate the findings from more detailed micro-simulation studies (i.e., AimSun + Autonomie) supports the use of the workflow for large scale analysis. All the tool deployment, linkage automation, process automation, code improvement and post-processing capabilities have served to greatly enhance the capabilities of using the workflow for large-scale studies, demonstrated this year through a set of 64 scenarios for four cities that was run under the SMART2.0 ANL (1C) project, where previously studies were only including 4 scenarios in SMART1.0. Ultimately, this makes the Workflow more capable for both large-scale research studies as well as for deployment to end-users and stakeholders.

Significant improvements to the vehicle-centric workflow (RoadRunner and SVTRIP) were also made. RoadRunner was more closely integrated with AMBER, providing greater flexibility and usability. A new graphical interface allows the user to create, modify, save, and visualize road scenarios, and the simulation post-processing capabilities were improvements. These new features are available in the first RoadRunner release, which was completed as part of the TCF project. SVTRIP was also integrated in AMBER, including a graphical user interface. In addition, new workflows to support research on CAV controls were created. A new automated calibration process that uses HPC and optimization to find the parameter values for maximum energy savings thus ensure proper energy savings assessment across scenarios. A case study showed it can increase the energy savings of a CAV eco-driving control by 6 percentage points. Finally, a new linkage with the traffic flow micro-simulation tool SUMO, which enabled the verification of functionality of CAV eco-controls in traffic situations (such as queues, cut ins) was implemented.

I.1.8 SMART 2.0 New Features (ANL)

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Project Introduction

The SMART Mobility modeling workflow that was previously developed linked many 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 expand the workflow to new 'anything in the loop' (xIL). capabilities

Objectives

Building on the project to improve and automate the workflow, this project will lead to the successful deployment of a significantly improved and expanded SMART workflow at a large scale to support many stakeholders as well as support studies in transportation systems and vehicle control. Primary objectives of the project in each main research area are shown in Figure I.1.8.1.

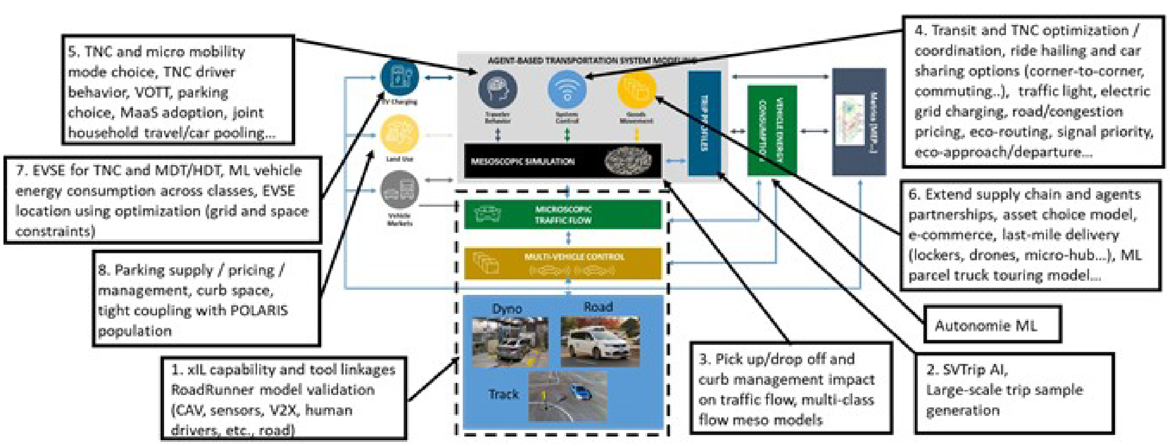

Figure I.1.8.1 Research objectives in each topic area

Approach

The work of this project will focus on model development and adding features to the SMART Mobility Workflow in eight primary task areas:

1. Expanding the workflow to xIL.
2. Development and validation of RoadRunner and SVTrip.
3. Improving traffic flow, transportation management, and connectivity simulation in POLARIS.
4. 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).
5. Expanding models of traveler behavior and induced demand under new mobility technologies.
6. Implementation of freight modeling with new technologies and a realistic simulation model of business firms that participate in goods movement.
7. Updating PEV charging models.
8. Modeling land-use, infrastructure, and transportation interactions in POLARIS and URBANSIM.

Tasks 1 and 2 focus on updating the RoadRunner-centered portion of the workflow dealing with vehicle controls, while Tasks 3-8 either expand existing capabilities or add new capabilities to the POLARIS modeling workflow. Tasks 3, 4, and 7 are focused on supply side modeling, and improve traffic flow, transit, and EV charging simulation in POLARIS. This will allow the project to explore the impact of connectivity, automation, infrastructure management, and management and optimization strategies for either mobility companies, public agencies, or both. Tasks 5 and 6 focus on the demand side of regional modeling, with Task 5 focusing on passenger travel behavior and Task 6 focusing on freight travel. The passenger behavior will expand work on VOTT changes, induced demand, impact of new travel modes, and long-distance traveling, driven by increased connectivity, automation technologies, and future mobility. The freight modeling work will continue to build out the development of the POLARIS agent-based freight model while allowing the framework to explore new trends in logistics, supply chains, delivery strategies and so on, as freight planning and vehicle technologies improve and expand. Finally, Task 8 is a joint task linking POLARIS to URBANSIM at a more detailed level than the linkage implemented in SMART 1.0, to improve population level consistency and allow more information to flow between each model when exploring future scenarios.

Results

Subtask 1 – New Anything-in-the-loop (XIL) workflow for dynamometer-based CAV controls testing

An “Everything in the loop (XIL) testing workflow” was developed, which enables to streamline the transition of energy-centric CAV controls from pure simulation in RoadRunner to experimentation in actual vehicles on a chassis dynamometer. To make this process reusable and automated, a new software architecture for XIL systems and integrated hardware-centric code within RoadRunner was developed. Most of the manual steps in the code integration, preparation and testing phases, were automated as shown in Figure I.1.8.2. Post-processing and quality check for analysis and verification of the controller functionality were also developed. The first iteration of the dynameter-based XIL workflow has been created and applied it to two vehicles via robot driver as the software-hardware control interface. With this workflow, the software part of the preparation of a test campaign only takes a couple days, making XIL testing robust and efficient. Due to the new XIL workflow, it was possible to demonstrate the functionality and energy performance of different kinds of ANL-developed CAV controls, on a BEV and ICEV, with V2I communications, and in scenarios mixing car-following and traffic signals. Overall, in this first year, there 207 successfully completed tests or 733 km of driving over only 17 dynamometer days.

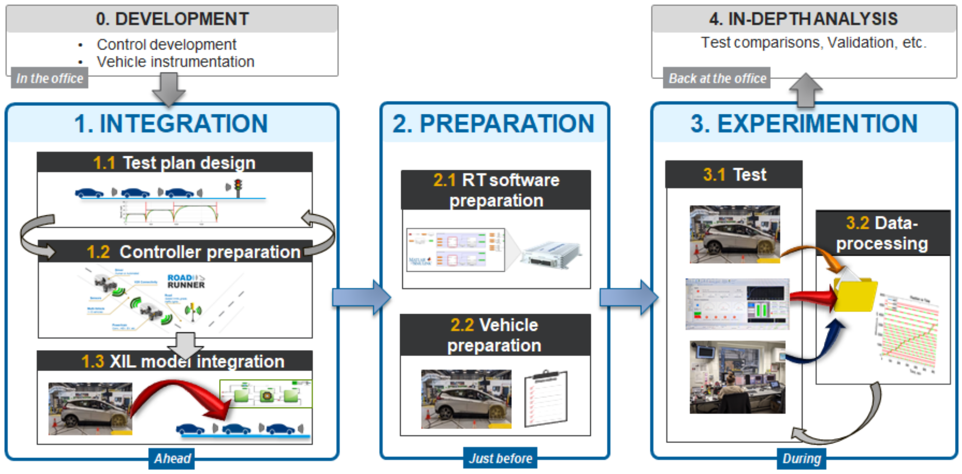

Figure I.1.8.2 Argonne XIL workflow extends SMART to hardware testing with highly automated steps

Subtask 2 – RoadRunner and SVTrip

New models for lateral dynamics impact on speed

Various components of RoadRunner were modified to model how lateral dynamics (turns, curves, ramps, etc.) impacts and constrains longitudinal speed, to make RoadRunner simulations more realistic and obtain more precise energy-related results. First, the capability of extracting curvature and heading information when importing real-world routes from HERE Maps into RoadRunner was added. Secondly, the Router and Perception model in RoadRunner were modified to convey the curvature signals. Therefore, a vehicle in RoadRunner can "see" the road curvature from a certain distance. Thirdly, a conversion model that processes curvature into maximum turning speed is placed in the vehicle control constraint block—this model was fitted to the public SPMD driving dataset. Finally, in the control module, the maximum turning speed is used to determine new effective speed limit and its starting position, and as a result, a curvature-aware vehicle controller is developed. This new model was demonstrated in RoadRunner simulations; as seen in Figure I.1.8.3, RoadRunner vehicles now adjust their longitudinal speed according to turns and curves.

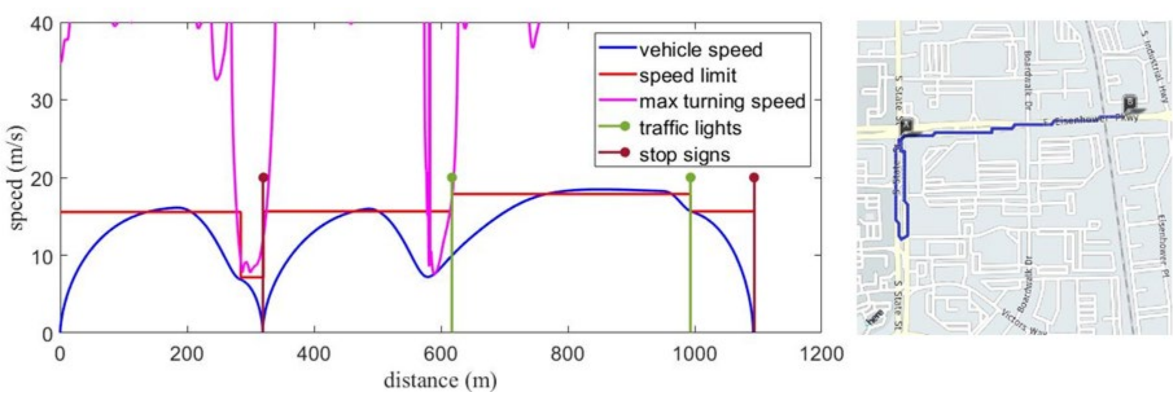

Figure I.1.8.3. Longitudinal dynamics impacts on longitudinal speed in RoadRunner – a simulated vehicle in RoadRunner adjust its speed to turns and curves based of the real-world route showed on the right

Realistic models of V2X communications and sensor integrated into RoadRunner

New models of sensors and V2X communications reflecting the realistic physical features and limitations were developed and integrated into RoadRunner. V2V messages from the new V2V model deliver a transmitting vehicle's position, speed, and acceleration information, corrupted by measurement errors. To consider failure in V2V message delivery, packet reception rates based on experimental data from the literature were modeled. The packet reception rates are varied with respect to distance gaps between two vehicles. In addition, communication latency is considered when a vehicle receives the V2V messages. The new sensor module in RoadRunner contains a long-range radar, a long-range lidar, and a front-view camera. The radar model provides a range to the front vehicle and the relative speed of the front vehicle. The lidar module gives a range to the front vehicle. The camera model is assumed to perceive the front vehicle's brake light and traffic signals. Each sensor module generates measurements with uncertainties determined by the distance to a detection object. The developed sensor and V2V models will be validated with experimental data when the data is available. Since both the V2V and the sensor modules provide information about the preceding vehicle, Kalman filters were developed to integrate the equivalent information. Moreover, low-pass filters are applied to reduce noise in radar and lidar measurements. The automatic installation in RoadRunner is enabled for the V2V connectivity, onboard sensor, and sensor fusion modules. Figure I.1.8.4 shows the results of a simulation featuring these models.

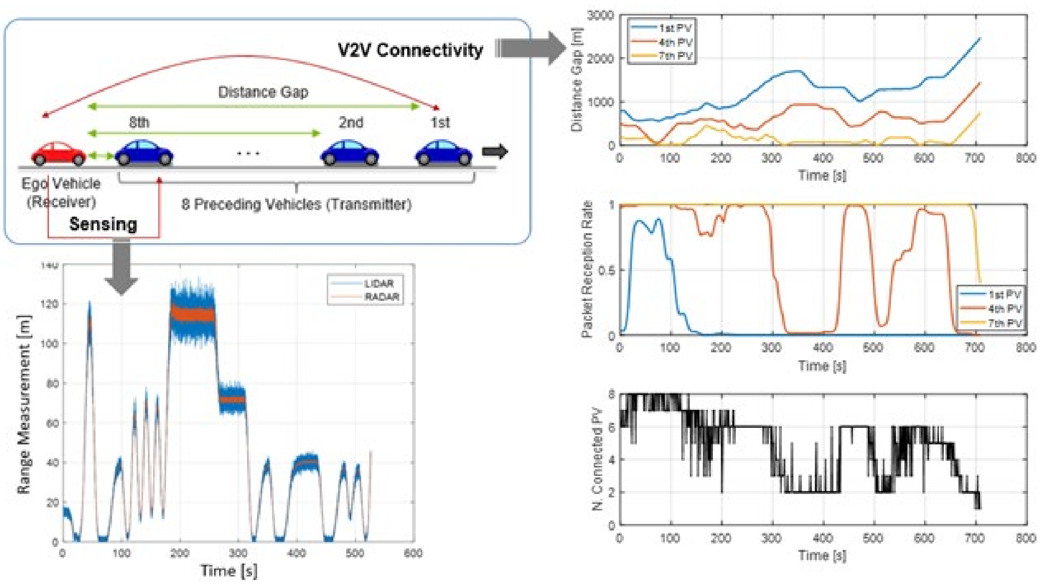

Figure I.1.8.4. Results from a RoadRunner simulation featuring the new V2X and sensor models. Simulated range measurement from LIDAR and Radar includes measurement noise, while the ego vehicle receives V2V information from a varying number of preceding vehicles, depending on their distance from the ego vehicle.

New AI algorithms identified for a faster and higher-fidelity SVTRIP

The algorithm behind SVTRIP is currently based on Markov chains (MC), which has limitations in terms of using the increasing number of attributes from real-world driving datasets. To overcome this barrier, an exploration of how Markov chains can be replaced by AI-based algorithms was undertaken. Various ways of using deep-learning (DL) were explored and a promising candidate that can generate stochastic speed profiles, similarly to what the MC-based algorithm does was identified. The DL algorithm includes a Convolutional Neural Network (CNN) originally developed for speech recognition (WaveNet). At each time step, the algorithm performs a regression to identify the most likely speed at the following time step, and an "error" is added using based on a secondary model that uses classification of the residuals. When generating many speed profiles of same length as validation dataset (real-world data), the DL-based algorithm approaches the dataset distribution relatively well, which demonstrates feasibility of DL as a replacement for MC.

Subtask 3 – Traffic Flow

This task focused on the development of models that supported the evaluation of connected vehicle applications in POLARIS. A road pricing model was implemented by extending the current capability of the existing router featured in POLARIS. The router already considered a generalized cost as the disutility to travel at that link (i.e., terms such as travel time and bus transfers are converted into monetary cost). One of these terms was already a monetary cost but was assumed to be fixed. This task consisted of changing the monetary cost of each link over time. Two different operation modes for time dependent pricing were added: (1) scheduled price per link read from the simulation inputs containing for each link the prices for each period of the day; and (2) a dynamic strategy that sets the cost based on the prevailing traffic state. The second main accomplishment was the development of a sensor and communication layer within POLARIS. This layer provides an abstraction to model the outcomes of Connected Vehicles sharing information through vehicle-to-infrastructure communication (V2I) and the spread and processing of this information including route suggestion. The connectivity module also can capture the impact of the fixed infrastructure (referred to as roadside units or RSUs) that is placed on specific link and position. Finally, fixed sensor such as loop detector or queue detector (e.g., through camera) that are independent of vehicle connectivity was also implemented. Along with these two developments, several tasks were completed or are underway which includes the development of a semi-microscopic (Lagrangian coordinates) traffic flow model, additional parameter and calibration strategy for traffic flow calibration, and the impact of pickup and drop-off operations by freight and TNC vehicles in the traffic stream.

Subtask 4 – Multimodal systems

This task seeks to explore ways to provide an energy-efficient, fast, and reliable door-to-door multimodal service to travelers. To achieve that goal, unconstrained micromobility operations and heuristic ride-hailing strategies for corner-to-corner pickup/drop-off were added to the multimodal travel model in POLARIS.

Unconstrained micro-mobility operations in POLARIS

Bike and scooter sharing services became an integral part of many cities in the world. To model them, firstly, the network representation in POLARIS was enhanced by adding the micro-mobility layer. Driving (vehicular) links always connect two driving nodes (intersections, ramps etc.). See Figure I.1.8.5 for the network representation in POLARIS. As a next step, the time-dependent intermodal A* (TDIMA*) algorithm in POLARIS was updated to find routes for four additional modes: 1) Undocked micromobility, 2) Docked micromobility, 3) Undocked micromobility and transit, and 4) Docked micromobility and transit. In the final stage, POLARIS multimodal simulation was updated to include micromobility actions such as biking, scooting, picking up a vehicle, and dropping off a vehicle.

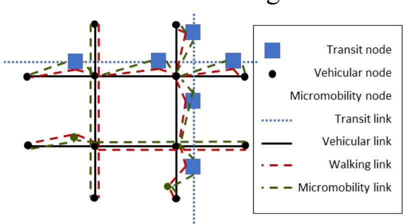

Figure I.1.8.5 Multimodal network representation

Implementation of heuristic ride-hailing strategies for corner-to-corner pickup/drop-off

Corner-to-corner pickup and drop-off (PUDO) was implemented for TNC vehicles in POLARIS through a heuristic in FY21. A subset of activity locations that exists in and used by all modes of travel in POLARIS were considered candidate corners for this strategy. Since activity locations are already used by traveler agents in POLARIS, travelers can walk to and from a location (like when travelers get out of their car, or deboard a bus). PUDOs forming a subset of these locations are, therefore, accessible and make for a great choice for PUDO locations. Figure I.1.8.6 shows the example set of stops used to aggregate trips to perform corner-to-corner routing. In FY22, link-level corners will be used to have more flexibility over vehicle and passenger routing. Use of links or intersections in POLARIS will bring positive outcomes of the heuristic tested closer to optimal.

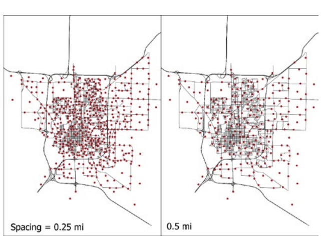

Figure I.1.8.6 Example use of stops for corner-to-corner routing

Subtask 5 - Demand

This task involved developing or improving multiple models relating to traveler behavior. First, an AV ownership choice model was estimated from a University of Washington stated preference survey that investigates how predicted market share of different vehicle ownership levels would change when adjusting trip-level and vehicle-level factors. A model of owning conventional vs. autonomous vehicles is also estimated based on expected utility for mode options for a daily tour, individual latent constructs (car dependency, AV trust), and mode characteristics. It explores the impacts of AV safety and trust vs. passenger safety in pooled rides. A solo vs pooled ride-hailing choice model was also developed that explores how future autonomous ride-hailing share is influenced by having a human versus a computer controlling the car. It investigates the additional market segments when looking at impacts of having a driver or not in an automated vehicle in comparison to a non-automated vehicle. The estimation dataset is developed through a fusion of CDOT ride-hail trip records, CMAP travel survey, and UW Uber API dataset. Mode choice modeling in POLARIS was also updated to represent the selection of shared bikes and shared e-scooters, first-mile-last-mile (FMLM) micromobility, and new multimodal transit structure. This work utilized the new Chicago travel survey data and the POLARIS multimodal router data to specify mode choice models. An FMLM micromobility choice model and e-scooter usage frequency model, shared e-scooter adoption model, and intention to continue e-scooter usage model were also developed, working with the University of Illinois at Chicago. All these models are being implemented to update the mode choice model in POLARIS. Finally, an improved VOTT model for connectivity and AV impacts based on a new round of survey data from the University of New South Wales was developed. It examines the impacts of AVs and multitasking using a stated preference survey.

Subtask 6 - Freight

In FY21, two major components were developed as part of the freight modeling framework, CRISTAL (Collaborative, Informed, Strategic Trade Agents with Logistics). The first component is the population synthesis model of firms and their member establishments (Figure I.1.8.7). The synthetic population contains the following attributes: firm membership, county (outside of region), detailed location (in region), number of employees, industry sector, input/output commodities, and commodity volumes. The population covers freight-intensive industries throughout the US and has representative international agents to enable global trade partnerships between the US and foreign entities. The population synthesis process is driven by data from the following sources: US Census, CoStar, Bloomberg, Yahoo, and the Securities and Exchange Commission (SEC).

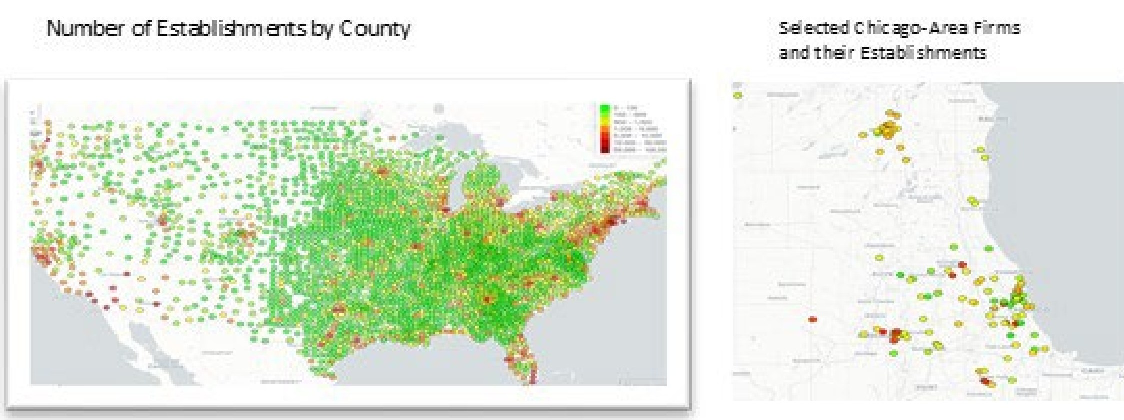

Figure I.1.8.7 Density of synthetic establishments in the US (left) and sample of firms and member establishments in the Chicago region (right).

Figure I.1.8.8 Selected suppliers from various regions for one buyer.

The second model component is the partnership model. First, the trade partnership model, which features a supplier selection process, was improved using real-world data. Second, the logistics partnership model, wherein firms that lack private fleets or distribution centers select logistics partners to provide these goods movement services, was developed and implemented. The trade partnership model is fundamental to generating origin-destination flows of goods, and the logistics partnership model is critical for simulating which fleet is transporting goods. The SMART 1.0 supplier selection model used "placeholder" model parameters, which were not based on data. These parameters were updated based on data from the US Commodity Flow Survey Microdata and the American Transportation Research Institute (ATRI). The model is rule-based, with larger companies selecting logistics agents that are also relatively large. The partnership model will be calibrated further in FY2022-FY2023 as the entire CRISTAL model is calibrated and validated.

Subtask 7 – EV Charging

Under SMART 2.0, POLARIS was extended to model the charging consumption of MD/HD vehicles. Moreover, POLARIS was integrated with a siting optimization algorithm developed by Michigan State University. To support real-time behavioral transportation models for individual charging decision-making, and rerouting of electric vehicles, a lightweight, efficient, accurate, and scalable EV consumption model has been developed by taking a machine learning approach. The data to support model training is generated from SMART 2.0 Autonomie + SVTRIP + POLARIS workflow. The model takes a sequence of links over a trip with vehicle and route level features, then predicts energy outcomes by estimating link-by-link energy values translated to battery SOC depletion. The model has been integrated into POLARIS for on-the-road agent query of energy demand and anticipated SOC depletion at link-level. Additionally, Michigan State University developed a charging station optimization algorithm that is used to locate EVSE for charging within POLARIS. The algorithm retrieves trip chains of all electric vehicles from POLARIS and determines at what trips and how much they would require charging. In the next stage, it determines the station location, plug types, and number of plugs to minimize the total cost of land acquisition, station, and plug investment—as well as the user costs of additional travel due to charging. The output of the algorithm was successfully tested on the Chicago Metropolitan Regional network in POLARIS.

Subtask 8 – Land Use

The primary focus of the land use modeling task over the previous year was on coupling the POLARIS and UrbanSim models through consistent population agents. While the software and workflow improvements needed to integrate the tools was handled under the 'SMART2.0 – 1A Workflow' project, this task was focused on ensuring that consistent agents could be represented in each tool. The ANL and LBNL teams developed design specifications for data requirements for population coupling. Pre-and post-processing tools were developed for the POLARIS model to read the UrbanSim outputs, convert the population elements from UrbanSim HDF5 files into POLARIS SQLite files and perform integrity checks. Models to estimate and/or impute missing values or characteristics of the households and individuals (i.e., employment industry, marital status), handle unplaced household from UrbanSim, and trigger POLARIS to call models normally handled by the internal population synthesizer (workplace location choice, vehicle selection). The model was implemented and tested for the Austin area, then used for an in-depth land use study of CACC impacts over time under the 'SMART2.0 – 1C Studies' project.

Conclusions

Over the previous year, substantial accomplishments have been made in expanding the features and capabilities of the SMART Mobility workflow. The core traffic flow algorithms in the POLARIS model have been expanded to account for vehicle-to-infrastructure connectivity, road pricing, and traffic signal controls. Additionally, a new formulation for Lagrangian coordinates-based traffic flow simulation has been implemented and is in the process of being tested to further expand the capabilities of traffic simulation in POLARIS to include car-following. The representation of multi-modal travel and new mode options in the simulator has expanded substantially. The base ride-share simulator now includes the use of ride-sharing vehicles as first-mile/last-mile travel options and represents additional fleet operational modes including corner-to-corner and on-demand shuttle operation. Micromobility options such as e-scooters and bike-share have also been added as new modes in the simulation. In addition, changes in demand driven by new mode options and other new mobility features have also been implemented, primarily in updates to the mode choice model to add the new options and choose between them (i.e., ride-hail vs. ride-pool, e-scooter vs other active modes). The representation of freight in POLARIS, through the implementation of the CRISTAL agent-based freight modeling framework, has also continued, with substantial progress in the firm synthesis and freight partnership components completed. The capability of modeling electrification of new and existing modes, such as TNC, transit, and freight vehicles has also been expanded. A representation of energy consumption and charging behavior was implemented in POLARIS and paired with a new optimization framework for EVSE siting to enable exploration of electrification. Finally, a significant expansion of the UrbanSim-POLARIS coupling for representing land-use and transportation interactions was undertaken, enabling consistent populations to be generated in UrbanSim and used in POLARIS. All the feature expansion and improvement that has been undertaken over the previous year has been demonstrated through individual studies and through the large-scale simulation study reported in the “SMART2.0 – ANL – (1C) Studies” project.

The all new XIL workflow enables the fast and robust transfer of controls developed in RoadRunner to real vehicles for testing on a chassis dynamometer. This new XIL workflow was put to practice to demonstrate the functionality and energy performance of different kinds of ANL-developed CAV controls on two different platforms with V2I communications, and in scenarios mixing car-following and traffic signals. The models for RoadRunner and SVTRIP were also improved. In RoadRunner, V2V communications can now be modeled. Additionally, all models of V2X receivers and sensors (radar, lidar, camera) feature imperfections common to these devices in the real-world, corresponding to degradation of the quality of the signal based on distance from the perceived/emitting object. The capability to model the effects of lateral dynamics (curves, turns) on longitudinal speed, e.g., slowing down before a turn was also added. These new capabilities improve the overall fidelity of RoadRunner and expand the use cases for the tool. Regarding SVTRIP, a new AI algorithm was developed to replace the existing statistical model, paving the way for a faster and higher fidelity SVTRIP in future years.

Key Publications

1. Cokyasar, T., F. de Souza, J. Auld, O. Verbas (2021). Dynamic Ride-matching for Large-scale Transportation Systems. Transportation Research Record. DOI: 10.1177/03611981211049422.

2. de Souza, F., O. Verbas, J. Auld (2021). ABM-LTM: A Link-Transmission-Model with Discrete Flows Able to Track Individual Vehicles. Presented at 100th Annual Meeting of TRB.

3. Dean, M.D., Gurumurthy, K.M., de Souza, F., Auld, J., and Kockelman, K.M. Synergies Between Repositioning and Charging Strategies for Shared Autonomous Electric Vehicle (SAEV) Fleets. Accepted for presentation at the Transportation Research Board Annual Meeting, 2022

4. Enam, A., J. Auld, T. Rashidi. “Do People Spend Travel Time the Way They Think They Would? A Comparative Study of Generic and Trip-Specific Travel Time Allocation Using Hybrid Multiple Discrete Continuous (MDC) Framework.” Submitted to Transportation (under review)

5. Gurumurthy, K.M., K. Kockelman. (2022) Dynamic Ride-Sharing Impacts of Greater Trip Demand and Aggregation at Stops in Shared Autonomous Vehicle Systems. Accepted for presentation at 101st Annual Meeting of the Transportation Research Board. Washington, D.C, January 2022.

6. Huang, Y., Gurumurthy, K.M., Kockelman, K.M., and Verbas, O. 2021. Shared Autonomous Vehicle Fleets to Serve Chicago's Public Transit Lines. Presented at the Bridging Transportation Researchers online conference in August 2021.

7. Jabbari, P., J. Auld, D. MacKenzie. "How Do Safety Perceptions and Car Dependency Affect Autonomous Vehicle Adoption?" Submitted to Travel Behaviour and Society (under review).

8. Javadinasr, M., S. Asgharpour, E. Rahimi, P. Choobchian, A. Mohammadian, J. Auld. "Eliciting Attitudinal Factors Affecting the Use of E-scooters Over Time: An Empirical Study in Chicago." Submitted to Transportation Research Part F: Traffic Psychology and Behaviour (under review)

9. Rahimi, E., M. Javadinasr, A. Davatgari, T. Brown, M. Mohammadi, A. Shamsiripour, A. Mohammadian, J. Auld (2022) Coupling Shared E-scooters and Public Transit: A Spatial and Temporal Analysis. Accepted for presentation at 101st Annual Meeting of the Transportation Research Board. Washington, D.C, Jan 2021.

10. Safari, F., A. Ardeshiri, J. Auld, A. Enam, T. Rashidi. "The Impact of Autonomous Vehicles and Multitasking on Value of Travel Time for Different Demographic Characteristics" Submitted to Transportation (under review).

11. Stinson, M., and A. Mohammadian. Introducing CRISTAL: A Model of Collaborative, Informed, Strategic Trade Agents with Logistics. Under review for publication, 2021.

12. Stinson, M., and A. Mohammadian. A Method to Integrate Strategic Alignment in Freight Transportation Behavioral Models. Under review for publication, 2021.

13. Stinson, M.; and Mohammadian, A. A Behavioral Model for Strategic Freight Transportation Decisions. Presented at the 2021 Transportation Research Board Annual Meeting.

14. Stinson, M., and A. Mohammadian. W2VPCA: A Method for Measuring Latent Strategies Using Existing Text Data. Stinson, M.; and Mohammadian, A. Under review for publication, 2021.

15. Stinson, M., and A. (Kouros) Mohammadian. Modeling Firm Transportation Strategy using Big Text Data. Proceedings of the IEEE Forum on Integrated and Sustainable Transportation Systems (FISTS), Nov. 3–5, 2020, in Delft, The Netherlands, pp. 365–371, doi: 10.1109/FISTS46898.2020.9264878.

16. Stinson, M., J. Auld and A. (Kouros) Mohammadian. A large-scale, agent-based simulation of metropolitan freight movements with passenger and freight market interactions. Procedia Computer Science, pp. 771–778 DOI information: 10.1016/j.procs.2020.03.157.Proceedings of the 9th International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTRANS-20), (virtual)

17. Tu, Y., P. Jabbari, D. MacKenzie, N. A. Khan. "Prospective Effects of Trip-level Characteristics on Autonomous Vehicle Ownership Choices in the US". Submitted to Transportation Research Part D: Transport and Environment (under review).

18. Verbas, O., J. Auld, M.R. Fissinger, S. Wainwright. (2022). Impact of Service Cuts, Telecommuting and COVID-19 Risk Perception on Transit Ridership, Traffic Congestion, Energy, Emissions, and Equity. Accepted for presentation at 101st Annual Meeting of the Transportation Research Board. Washington, D.C, January 2022.

I.1.9 SMART 2.0 Studies (ANL)

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Start Date: October 1, 2020 End Date: September 30, 2021
Project Funding: $1,265,000 DOE share: $1,265,000 Non-DOE share: $0

Project Introduction

Many diverse new technologies have disrupted transportation, and they are expected to continue to do so soon. Their long-term impact and interactions with existing systems remain largely unknown. As a result, both public (e.g., MPOs, cities) and private (e.g., automotive, mobility, suppliers) organizations face uncertainties when committing to long term investments and adopting solutions

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 travel time [VOTT], connectivity, etc.) primarily relied on assumptions rather than data-driven models of future behavior.

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...) and how they collectively affect the entire transportation system.

Approach

Each core research area with the SMART Mobility space has a task focusing on energy and mobility research questions that are domain-specific, including:

- What impact could ‘shared mobility’, micromobility, and multi-modal travel have on transit operations and overall transportation system efficiency? (Task 3 – Multi-modal).
- How will passenger travel behavior (incl. VOTT), change in response to new technologies? (Task 4 – Behavior).

- How will the ongoing reorganization of consumer goods distribution and new technologies in freight delivery impact regional mobility and productivity? (Task 5 – Freight).

The remaining tasks adopt the systems view to quantify the impacts across technologies to answer key questions, including:

- What are the integrated supply and demand impacts of consumer goods distribution, ride hailing, and other new technologies and how are they operated most efficiently considering joint effects? (Task 1).
- What system controls and connectivity features governing transportation supply and usage can be implemented by cities, fleets, and others to improve system efficiency? (Task 2).
- How could electrification across passenger cars and fleets be implemented and what will be the impact? (Task 6).
- What is the impact of new technologies (for both passenger and freight) on land use? (Task 7).

Finally, Task 1 combines features of all the other tasks into large scale scenario analysis applied to multiple cities. Scenarios will be designed in collaboration with SMART consortium laboratories, DOE, industry, and other external stakeholders to highlight interactions between different technologies and behaviors.

This individual and large-scale studies are intended provides insights validated through targeted deployment that will be shared with the transportation stakeholder community through various means.

Results

System Control

This subtask focused mainly on the applications that are enabled by or will likely be improved by the emergence of connected vehicles with the goal to assess the impact of connectivity on urban mobility. Two different studies were considered, Active Demand Control and the mitigation of non-recurrent congestion through vehicle connectivity. For the Active Demand Control, a road pricing model was implemented and applied using different schemes for pricing in the city of Austin, TX. The strategies considered were: (1) baseline (prices only on the current HOT lanes); (2) per mile price (VMT cost); (3) cordon-pricing; and (4) a time dependent delay-based link-specific design to price and therefore reduce delays in the network. The main results are depicted on Table I.1.9.1. The delay-based design outperformed all other strategies leading to a reduction in 10% on VHT and energy consumption.

Table I.1.9.1 Pricing Scenario Results

Scenario	WMT (million mi)	WHT (million hr)	Speed (mph)	GHG (tons)	Energy (MWhr)	Revenue ($)
Baseline	42.6	1.63	26.1	372.8	1129.4	$19.91k
Congestion pricing	42.9	1.48	29.1	359.1	1087.9	$1.44M
Fixed price	42.2	1.60	26.0	369.9	1120.5	$1.44M
Cordon pricing	41.7	1.61	26.2	370.0	1120.7	$348.74k

Table I.1.9.2 Connectivity Scenario Results

#RSU's	% connected	% informed	VHT(K)	Speed (mph)
5%	25	25	1950	25.43
25%	25	25	1879	26.37
100%	25	25	1866	26.55
5%	50	50	1851	26.82
25%	50	50	1769	28.03
100%	50	50	1747	28.39

The mitigation of non-recurrent congestion enabled by Vehicle Connectivity and sensing was studied in Austin, TX. To support this task, the replication of traffic incidents specified by link, duration, and capacity scale (impact) was added into POLARIS. For the experiments, incidents (synthesized based on real data) were introduced, and results were compared to baseline simulation runs. The incidents increased travel time by 30% in the worst-case scenario, consistent with real-world estimates of 45% the delays being due to non-recurrent congestion. Different penetration rates of informed and connected vehicles were tested with drivers updating their routes according to the information shared by the connected vehicles in the network. Table I.1.9.2 summarizes the result. In summary, connectivity has the potential to mitigate congestion by suggesting better routes to connected and informed vehicles.

New Modes

This task involved collaboration with the Chicago Transit Authority (CTA), and Regional Transportation Authority (RTA) that coordinates the Chicago region's transit system to explore transit optimization. There are 3 major transit agencies in the region: CTA (urban rail and bus), METRA (commuter rail), PACE (suburban bus). And there is an additional commuter rail line called South Shore Line operated by the Northern Indiana Commuter Transportation District (NICTD) that connects the city center to South Bend, IN. Other than the baseline, four major scenarios were run: "Baseline + BRT" introduces two additional Bus Rapid Transit lines to the existing service, whereas "2x" doubles the frequencies for a transit line but only at half-hour intervals when the line is in service. "2x + BRT" combines the two. To facilitate the "optimized" scenario, an initialization scenario was run where a transit line operated at all time intervals resulting in an operational cost that is 407% higher than the baseline. This enabled the estimation of the latent demand using POLARIS ABM modeling. With that input and with a budget of 50% higher than the baseline, the frequencies were optimized. As seen in Table I.1.9.3, adding frequencies is marginally beneficial to CTA given that it already serves a high frequency service when needed. Adding new routes—in this case 2 BRT lines—causes more ridership increase for CTA. On the other hand, METRA commuter rail could substantially benefit from running more frequent service. Finally, the optimized scenario can achieve with 50% additional operational budget what the 2x scenario can achieve with 100% additional budget.

Table I.1.9.3 Number of Boardings under Different Scenarios

	Base (000)	Base + BRT (000)	2x Freq. (000)	2x Freq. + BRT (000)	Optimized (000)
CTA Bus	787	834	900	948	807
CTA Rail	711	776	711	746	793
METRA Rail	278	288	338	365	390
PACE Bus	137	142	207	237	125
SSL Rail	6	6	5	6	7
TOTAL	**1,919**	**2,045**	**2,162**	**2,302**	**2,122**

Behavior

Several studies were conducted under the behavior task this year. The first investigates how traveler decisions are affected by the value of travel time (VOTT) from connectivity and automation. The study utilized a choice experiment survey to analyze how VOTT varies in different contexts. It was found that AV VOTT demonstrates a lower sample mean for mandatory trips over non-mandatory trips. This is also true across all socio-demographics such as gender, age, and income categories. These findings were explored in a simulation analysis for different penetrations of CACC. Scenario results suggest that there is minimal impact in the traffic network from CACC traffic changes alone. Network load is found to reduce slightly with CACC, however, increase significantly if VOTT changes are considered. Mobility metrics improve marginally with CACC, but effect is reduced when VOTT is considered. For instance, moderate improvement in vehicle and trip speeds is observed when considering only traffic flow impacts of CACC, but not much change is found between 40-65% penetration. However, when considering VOTT impact on highways overall travel increases from 4.9% to 6.5%. Also, drastic increase in congestion is observed with 24% increase in travel times. Finally, energy analysis results indicate that CACC deployment does not affect energy use significantly when considering traffic flow alone. When considering VOTT effects, impacts of extra congestion drop MPG by 5.8% to 6.5%. Results also demonstrate that without the traffic flow performance improvement from very high penetration of CACC, the impact on fuel consumption would be much worse. A second study exploring the impacts of 'first-mile-last-mile' (FMLM) ride-share trips on mode choice behavior in POLARIS was also conducted. In this analysis, it was found that FMLM service raises transit use from 5.4% to 6.3%, and that the ride share fleets are serving 12% more requests with only 4% increased VMT compared to door-to-door (D2D) service only.

Freight

Off-hours delivery (OHD), in which trucks make deliveries overnight (other off-peak times), is proposed to reduce systemwide congestion and energy consumption while reducing costs for shippers, receivers, and delivery fleets by reducing drive times and fuel use. OHD has only been studied in deployments involving a few participating firms. The comprehensive, regional impacts on congestion and energy have not been analyzed using a regional, systems simulation approach. The objective of this study was to quantify the regional energy and mobility impacts of business-to-business (B2B) off-hours delivery, evaluating the effects of both (1) receiver willingness-to-accept (RWTA) off-hours deliveries, and (2) local municipality policies that affect OHD. The Chicago Metropolitan Agency for Planning (CMAP) provided guidance for the study and provided data from a 2014 survey on municipality overnight delivery policy that the agency conducted. RWTA was determined based on industry classes from a previous study by Rensselaer Polytechnic Institute (RPI). The study found that in the baseline, both MDT and HDT travel mostly during the daytime hours. In the OHD scenarios, approximately 5% to 6% of MD and HD trucks (about 220,000–240,000 trips total depending on the scenario) shift their delivery time to overnight. Table I.1.9.4 shows the simulation results for the baseline and scenario runs. In the OHD scenarios, MDT (HDT) VMT decreased by 1.8%–2.1% (2.9%–3.1%) while MDT average speed increased by 7.6%–8.6% (2.4%–2.8%), indicating that trucks were able to take shorter paths and faster when traveling overnight (compared to daytime travel). OHD also generated fuel savings (2.4%–3.2% for MDT and 3.6%–3.8% for HDT) as the result of shorter trips and increased speeds. The results suggest that by relaxing policies that restrict OHD, improved results for VMT, speeds, and fuel savings can be obtained. Round-the-clock operations can also benefit fleets by enabling greater utilization of vehicles.

Table I.1.9.4 Simulation Results: System-wide Mobility and Energy Metrics

		Values			%Diff (vs. Baseline)		
Mode	Scenario	VMT	Speed (mph)	Fuel (kg)	VMT	Speed (mph)	Fuel (kg)
MDT	Baseline	2,668	33.4	871			
	Scen. 1	2,612	36.3	857	2.1%	8.6%	3.2%
	Scen. 2	2,620	36.0	883	1.8%	7.6%	2.4%
HDT	Baseline	20,960	51.2	10,515			
	Scen. 1	20,313	52.7	10,470	3.1%	2.8%	3.8%
	Scen. 2	20,356	52.5	10,392	2.9%	2.4%	3.6%

Autonomous and electric vehicle technologies may enable increased OHD by making delivery quieter at nighttime and less reliant on night shifts for drivers.

Land Use

The behavioral studies for CACC demonstrated the influence that the change in VOT can have on overall mobility outcomes, but it was implemented as a fixed-point scenario. To demonstrate the dynamic interactions between mobility changes from new technologies and land use, the study was rerun using the integrated UrbanSim-POLARIS workflow for the Austin region. In the study, the penetration of CACC vehicles evolved over time, with rates of 0% in 2015 increasing to 75% in 2035. The land use was allowed to evolve over time with runs for every year from 2010 to 2035, with the POLARIS model run every fifth year to generate new travel skims. The skims were modified based on penetration of CACC by zone to represent the impact of VOTT changes. Overall, the population in the region grew by 58% between 2015 and 2035, and speeds reduced by 16% in the baseline, driven by a 25% increase in total travel miles, although per capita travel was reduced by 21% due to new development and increased congestion. However, when CACC deployment occurs, total travel is increased by 37% (a 50% increase over the scenario with no CACC) and average speed drops by 26%. This occurs as the reduced travel cost due to CACC allows for longer work trips—influencing the overall urban form and network performance, as demonstrated in Figure I.1.9.1. In fact, work trips are as long in 2035 under the CACC scenario as they are in the base year, while without CACC work trips would by 15% shorter on average.

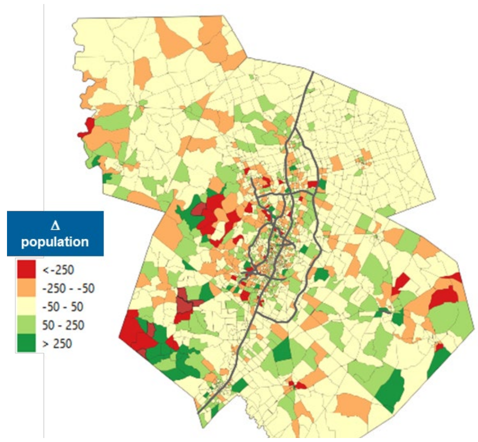
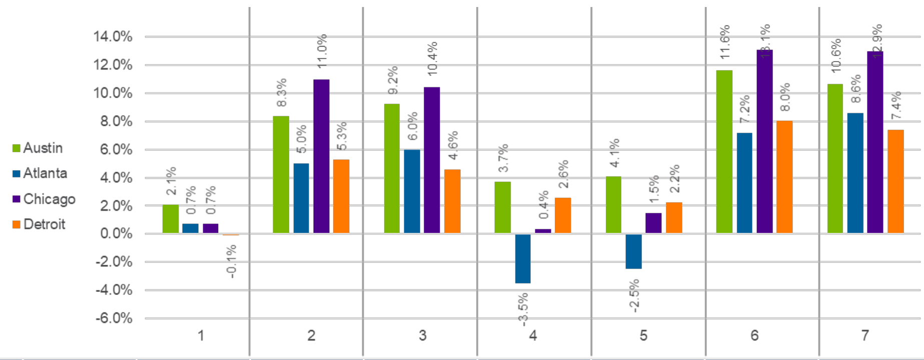


Figure I.1.9.1 Δ population in 2035 in CACC vs no-CACC scenario

Main Studies

The preceding studies were designed to explore technologies, policies, and other strategies for various transportation system components. However, in each case these were run for individual concepts in isolation and generally only for one city or region. However, the overarching goal for the SMART Mobility system-of-systems approach using the workflow is to explore the interactions of multiple technologies and explore more optimal solutions. Therefore, a large-scale study that combines four of the above studies in a design of experiments and applies it to four regions (Atlanta, Austin, Chicago, Detroit) was conducted. The individual features explored were CACC deployment with value of travel time changes, road pricing using a delay-based congestion charge, vehicle connectivity using road-side units, and off-hours freight delivery. A combinatorial design with each of these features either turned on or off gave a total of 16 runs for each city and 64 runs overall. The impacts of the various combinations of technologies where then compared across cities, as shown in Figure I.1.9.2 for the network speeds.

Figure I.1.9.2 Scenarios impacts on speed for different combinations of technologies



Scenario ID	0	1	2	3	4	5	6	7
RSU/CV%	0	0	0	0	0	0	0	0
CACC/VOT	Base	Base	Base	Base	75% / HIGH	75% / HIGH	75% / HIGH	75% / HIGH
ROAD PRICE	Base	Base	Delay-based	Delay-based	Base	Base	Delay-based	Delay-based
OFF-HOURS	0	5% shift	0	5% shift	0	5% shift	0	5% shift

Key findings from the scenario analysis include:

- Impacts of different technologies vary substantially by city. For example, CACC increases VMT by 2.5% in Chicago but does not increase it at all in Austin, due to differences in activity distributions and network congestion.
- Road pricing has the overall highest impact, ranging from a 5% increase in speed in Atlanta to an 11% increase in speed in Chicago, mostly related to the baseline congestion levels.
- CACC had smaller marginal impacts, with total travel increasing in some cases (Chicago, Detroit), congestion improvements only (Austin) or congestion getting worse (Atlanta).
- Roadside units and vehicle-to-infrastructure connectivity do not have an impact in average day conditions.
- Off-hours delivery leads to consistent improvements in speed under all scenarios.

Notably, the study identified several key interaction effects that could not be identified in analysis of individual technologies. It was found that the impact of off-hours delivery was reduced under road pricing scenarios as both can cause temporal shifts which counteract to a degree. Additionally, CACC and road pricing can interact in complex ways to cause additional benefit greater than the marginal impact of each technology. As an example, in Chicago CACC alone increases hours travelled by 2.1% while pricing alone decreases hours travelled by 14.2%. However, the combination of CACC with pricing decreases hours travelled even more, by 14.7%. Overall, the combination of CACC, road pricing without off-hours delivery was identified as the best performing scenario in terms of overall mobility metrics.

Conclusions

This project involved running many scenarios for different transportation technologies, behaviors, strategies, etc., both individually and in combination. The scenarios were built upon capabilities added in the "SMART2.0 1B – New Features" project and enabled by the computational and process enhancements from "SMART2.0 1A – Workflow" project. Individual scenarios regarding traffic flow included a study of road pricing, where it was determined that delay-based road pricing outperformed all other strategies leading to a reduction in 10% on VHT and energy consumption, and a study of roadside connectivity showing that even moderate penetration rates of roadside units with 25% penetration of connected vehicles can recover about 50% of the delay induced by random incidents. A study on transit optimization demonstrated that the potential for increasing ridership is much more efficient with introducing new service in targeted areas versus broadly increasing service frequency, especially in high-frequency systems like the Chicago Transit Authority. The impact of CACC and VOT change was demonstrated in a behavioral study where it was found that overall mpg is reduced up to 6.5% with additional travel from CACC owners more than negating any traffic flow benefits. A study of off-hours freight delivery was also performed that showed the shifting of 5–6% of deliveries to overnight hours could benefit both delivery fleets, due to a 2.3% increase in heavy duty truck speeds and a 7–8% increase in medium duty speeds, as well as the larger transportation system. The CACC VOTT study was also paired with a land use impact study to demonstrate the dynamic impacts of VOTT changes over time. Finally, many of the above analysis were combined into a large-scale scenario analysis, where CACC, connectivity, pricing and off-hours delivery were explored in various combinations for four cities. Varied impacts were identified in each city, with the combination of CACC and road pricing generally found to perform the best under the modeling assumptions specified.

Key Publications

1. Cokyasar, T., J. Larson, and M. Stinson. Solving Massive-Scale Service-Time-Constrained Capacitated Vehicle Routing Problems. Accepted for presentation at the Transportation Research Board Annual Meeting, 2022

2. Cokyasar, T., M. Stinson, O. Sahin, N. Prabhakar, and D. Karbowski. Optimizing Fulfillment Center Locations for Regional Last-Mile Drone Delivery. Submitted to Transportation Research Record.

3. Huang, Y., Gurumurthy, K.M., Kockelman, K.M., and Verbas, O. 2021. Shared Autonomous Vehicle Fleets to Serve Chicago’s Public Transit Lines. Presented at the 3rd Bridging Transportation Researchers Online Conference.

4. Sahin, O. and M. Stinson. Off-Hours Delivery: Simulated Systemwide Results for the Chicago Region. Accepted for presentation at the METRANS International Urban Freight Conference (I-NUF), 2022.

I.1.10 Real-Sim: An XIL Platform for Mobility Technologies (ORNL, ANL)

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Project Funding (FY20): $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 and modeling of 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 advanced driver-assistance systems (ADAS), connected and autonomous vehicles (CAVs), their surrounding environments, traffic networks, traffic control, and the various scenarios that greatly effect each one of these. Furthermore, traditional research and development (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 x-in-the-loop (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

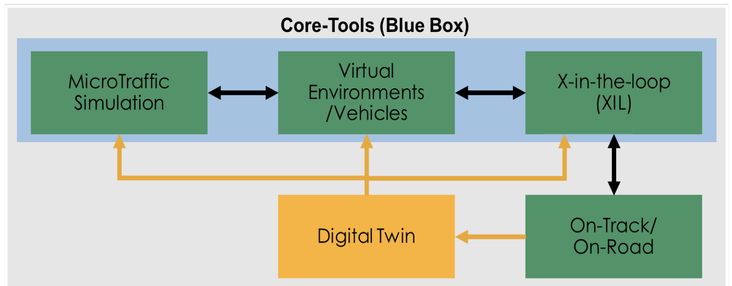

Figure I.1.10.1 Real-Sim concept for combining the scaled resources with for validating these tools at varying system levels.

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 (VSI) and new Connected and Automated Vehicle Environment (CAVE 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 development 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 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, GNSS, V2X, etc.) as well as XIL interfaces between virtual sensors and their corresponding real controllers/hardware (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, enhancements to include SPaT, V2X, and traffic control XIL applications

This task enhances the traffic microsimulation capabilities of the VPPG to include SPaT, V2X, and traffic control. These enhancements will add 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; a flexible XIL platform capable of performing the complex “transportation as a system” co-simulation.

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 experiment data 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 vehicle-based platform will provide independent data collection from production sensors and installed sensors (imaging, 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 signal broadcasts 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 like 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. The vehicle used to collect this data will be the ANL data collection vehicle from task 1.3 and/or the ORNL RAV4 mule.

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 this year included developing the Robotics Operating System (ROS) code necessary to access the appropriate data from IPG CarMaker, map the sensor data from the CarMaker data structure into the appropriate ROS topic, and publish the necessary ROS topic. With support from IPG, ORNL was able to implement a CarMaker/ROS integration that execute multiple sensor models in IPG Carmaker and broadcast the data in real-time to the RAV4 perception stack. The methodology for constructing this sensor interface was constructed with an emphasis on raw data interfaces between the sensor models of a virtual environment (i.e., IPG Carmaker) and the ROS drivers consuming the sensor data on the perception stack. Additionally, the example was extended by developing sensor integration ROS code for the GPS and IMU to publish their information out to the ROS network (Figure I.1.10.3). An example of this can be found in Figure I.1.10.4

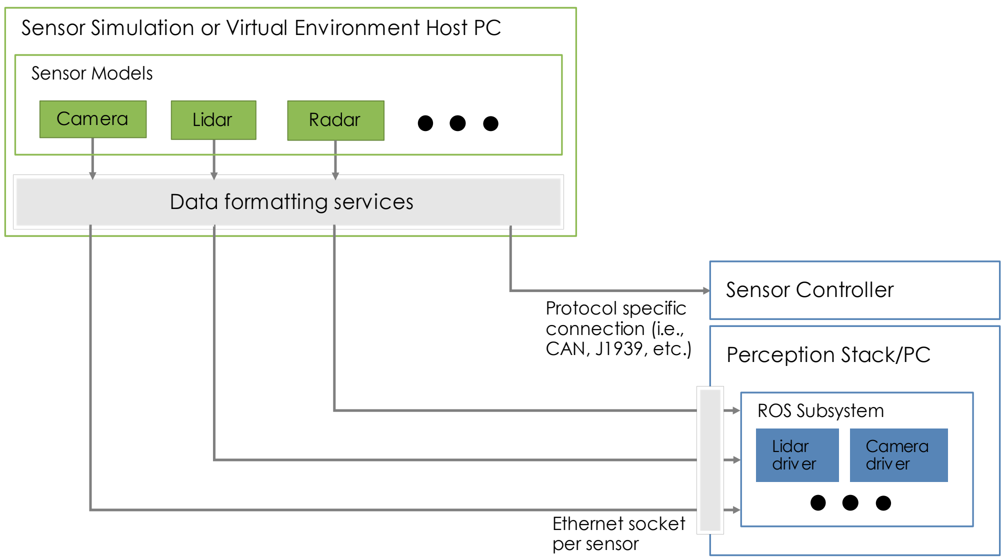

Figure I.1.10.3. This diagram outlines the sensor communications methodology for broadcasting sensor model data from the virtual vehicle environment to the RAV4 perception stack.

Additionally, an IPG CarMaker RAV4 vehicle model had to be created and matched to the specifications of the Toyota RAV4 mule vehicle to match the vehicle geometry such that the sensor mounting points in the simulation would be like the real mule vehicle.

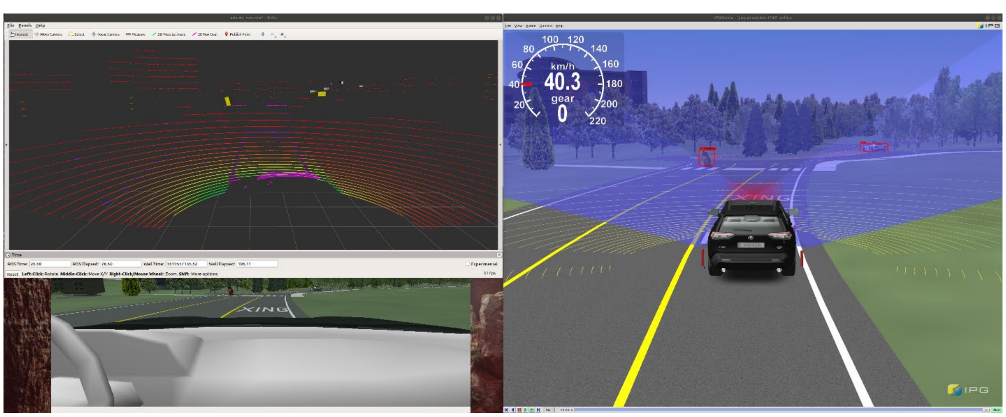

Figure I.1.10.4. Rviz displays the lidar visualization on the top left including markers from the camera object detection routine in CarMaker. Also, the camera output is visualized on the bottom left.

Subtask 1.2: Integrate SPaTs and other traffic control devices into the Real-Sim

A SUMO traffic microscopic simulation of 4 intersections along Shallowford Rd in Chattanooga, was built and modified based on existing efforts from the EEMS Regional Mobility project. Signal Phasing and Timing (SPaT) data of these intersections was implemented in the SUMO simulation. Then to test XIL functionality of for traffic control devices, real-world signal controllers, configurations, and SPaT data of the intersection of Shallowford Rd and I-75 Southbound Ramp was deployed to a physical Siemens M60 Advanced Traffic Controller. During this proof-of-concept test, real-time two-way communications between the M60 controller and SUMO simulation were achieved at 0.1 s intervals with minimal latency. The overall architecture is shown in Figure I.1.10.5, the flexible Real-Sim interface is used as the bridge between SUMO traffic simulation and the M60 Signal Controller. The Real-Sim interface has a Traffic Layer that handles communication directly with SUMO, and an Application Layer which handles specific communication required by the application. In this case, it is a signal-controller-in-the-loop implementation. The M60 controller uses the NTCIP server, an existing effort between ORNL and Siemens as part of the Regional Mobility project, to communicate with the Real-Sim interface, which is set up to (1) receive information from SUMO; (2) send instructions to M60 controller; (3) get status information from M60 controller; and (4) send controller status information to SUMO.

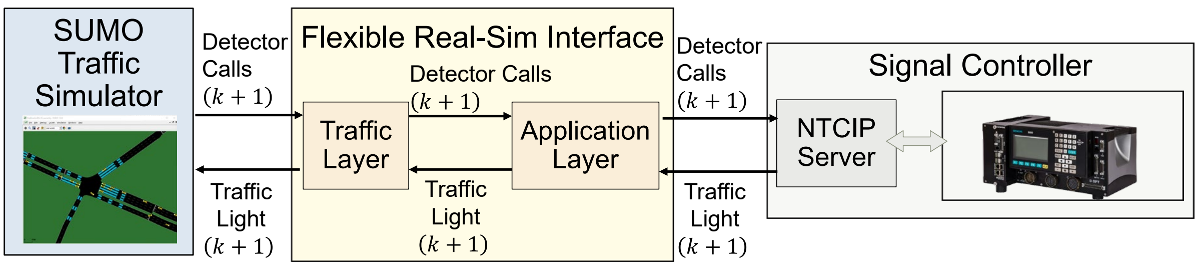

Figure I.1.10.5. Architecture of the Signal-controller-in-the-loop Simulation

Specifically, detectors in SUMO simulation, when triggered by virtual vehicles running in the SUMO simulation, will send vehicle calls to the M60 controller, and the M60 controller will respond to these calls as if it receives real vehicle calls from real-world detectors; meanwhile, the program shares the active status (i.e., green, yellow, and red) of each phase to SUMO at 0.1 s intervals (can potentially be even faster but will need more testing). Figure I.1.10.6 shows screenshots taken during the actual implementation.

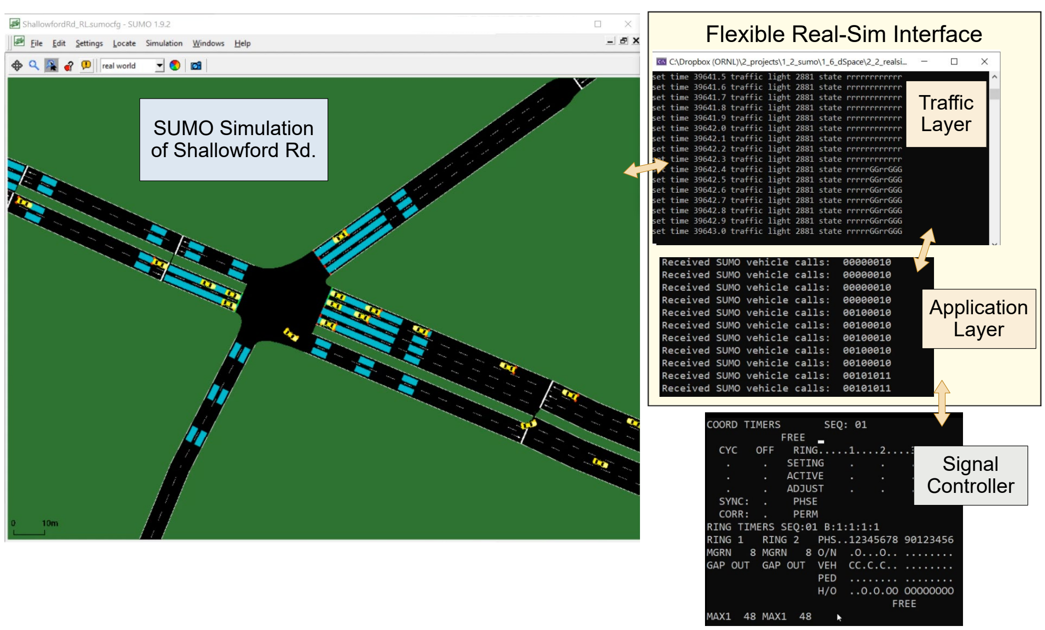

Figure I.1.10.6. Screenshots of the Actual Signal-controller-in-the-loop Implementation

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

This year ANL started development of Vehicle Components of Mobile DAQ platform using on Autoware AI open-source software on vehicle mounted PCs. Collaborative SMART research efforts using the Mobile DAQ, including those listed in this report as well as others such as the light duty on-road CAV study, require data collection of either unique signals, or from sensors, that are not standard for collection in the CARMA or Autoware platforms. Modifications continued through the last quarter to modify the Autoware AI based platforms to capture datasets in a format needed for the corresponding research efforts. For this project large modifications were made to the system including multiple iterations of calibration of the sensor fusion (LIDAR/ vision) system, restructuring of the vehicle mounted camera software, installation of a radar mounted to the front license plate bracket for a greater front field of view, fabrication of a LATCH system mounted compute rack, and other upgrades to the system to ensure it is safe for roadway testing. The updated proof of concept system can be seen in Figure I.1.10.7. Commencement of on-road data collection efforts with mobile DAQ on a Cadillac CT6 was performed and refining and modifying the vehicle component systems based on results from on-road testing was evaluated. Lastly construction of the proof-of-concept infrastructure component was begun. The base portable system for development is a JTI 'Sentinel' traffic light. The system was modified to include a Cohda Mk5 DSRC radio, hardware for computing, and a 360 camera for collecting video data at the test location.

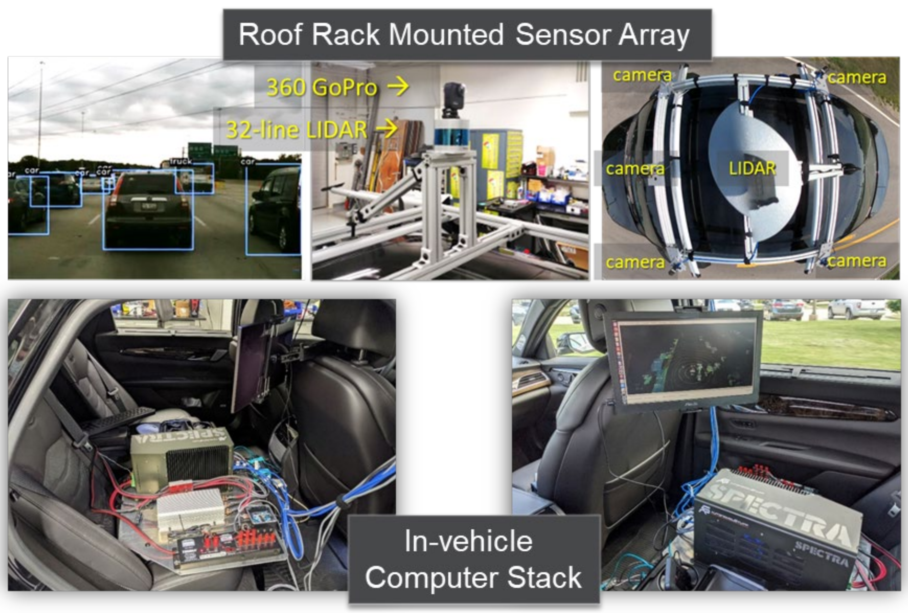

Figure I.1.10.7: The proof-of-concept ANL AMTL Mobile DAQ vehicle component includes a portable roof rack mounted sensor array connected to a compute stack located in the vehicles rear seat.

Conclusions

This being the first year of the project, much of the work performed was mostly setup for the more application driven or data driven work that will occur in years 2 and 3 of the project. However, there was significant accomplishments in the areas of sensor emulation, development of the Mobile DAQ platform, and the addition of HIL methods and interfaces to traffic control devices. The important steps forward in the next two years are to mature the sensor emulation interfaces and Real-Sim Framework enough that they can be easily applied to real-world conditions and scenarios for validation of advanced vehicle technologies and EEMS projects.

Acknowledgements

ORNL would like to thank David Anderson, Erin Boyd, and Danielle Chou as the DOE EEMS Program Manager and Technology Mangers, respectively and their continued support on this project.

I.1.11 Optimizing Drone Deployment for More Effective Movement of Goods

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Project Funding: $1,200,000 DOE share: $1,200,000 Non-DOE share: $0

Project Introduction

Aerial drones offer a distinct potential to improve the delivery of goods in the last mile, especially for time-sensitive, small, and localized deliveries. However, there is a need to understand what the energy consumption for drone deliveries is, 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 allow 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 drones for goods delivery by generating insights on:

- Impacts of restricted 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, and charging that meet the needs of various users.
- The total energy and time needed to deliver packages by drones compared to ground-only vehicles in several 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 drones.

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.

See Figure I.1.11.1 for a representation on how these elements interact.

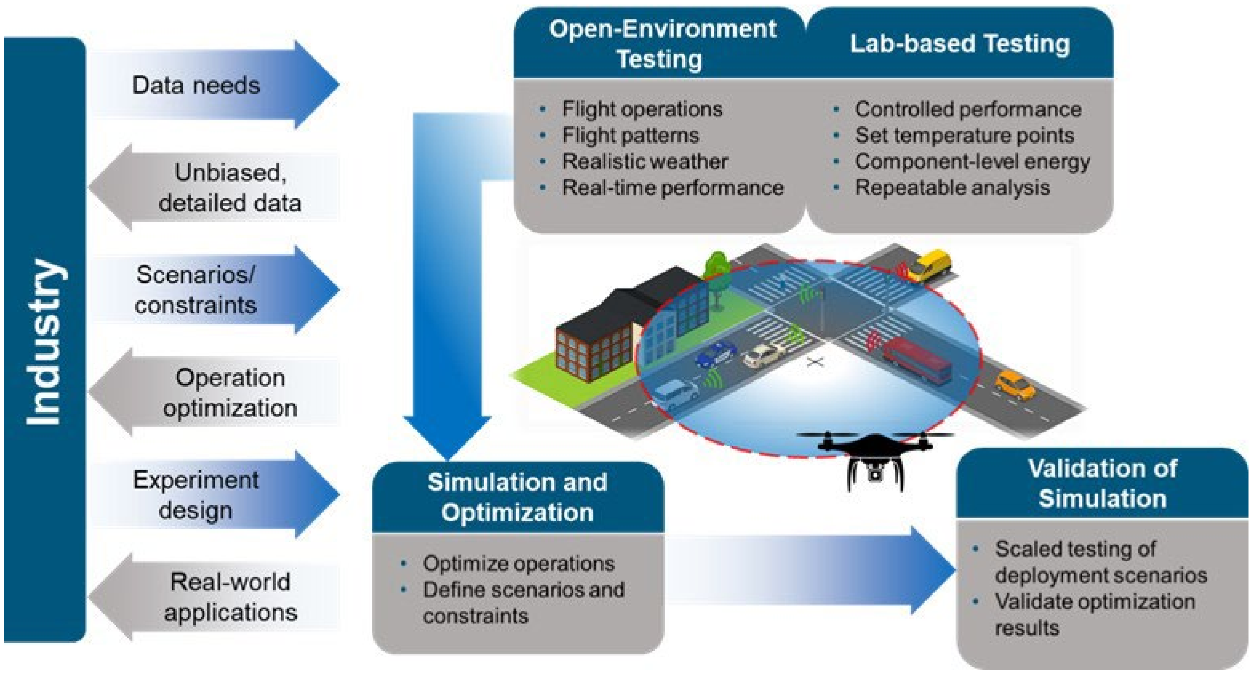

Figure I.1.11.1 Approach to drone optimization.

Results

During FY 2021, the project worked with industry and academic partners to complete an analysis of the current drone delivery industry and produce several scenarios to evaluate. From all the scenarios considered, three scenarios were chosen for modelling and optimization. Scenario 1 is a direct delivery of goods from a single location to the consumer—such as a delivery from a store or distribution center to a home. Scenario 2 is a direct business-to-business delivery between two business locations, where the drone can be charged and dispatched from either location—such as store to store or distribution center to store deliveries. Scenario 3 is a delivery as a service model where the drone is dispatched to pick up an item from one location, deliver it to the consumer, and return to its base location. Scenarios 1 and 2 are a variation of direct delivery (left side of Figure 2) and scenario 3 is a variation of indirect delivery services (as shown on the right image in Figure I.1.11.2).

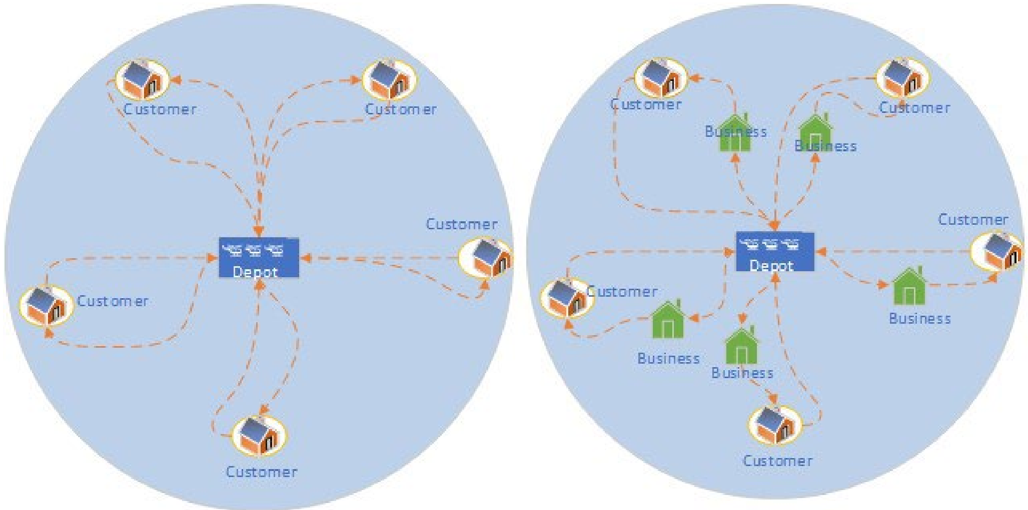

Figure I.1.11.2: Direct delivery (Scenario 1 and 2, left) and service delivery (Scenario 3, right).

Two different drones were tested in a laboratory and outdoor environment to characterize their package delivery performance. The first drone was the DJI Matrice 600 Pro. It is a hexacopter drone with an empty weight of approximately 21 pounds (lbs.), including batteries, and can carry up to 13 lbs. of payload at a maximum airspeed of 40 mph.

The second drone was the UAV Systems International Tarot 650. It is a significantly smaller quadcopter drone with an empty weight of approximately 7.8 lbs., including battery, and can carry up to 3.3 lbs. of payload at a maximum airspeed of 32 mph.

For in-field testing outdoors, both drones were instrumented with a sensor platform to record key operation data and environmental conditions. The collected data included total energy use, GPS location, inertial measurement unit (IMU) data, ambient temperature, ambient pressure, wind speed, and wind direction.

A set of experiments were designed to test the impacts of different payload weights and flight operations for each drone. The test plan included the following tests:

- Ascent to Height: Vertical ascent to desired height, hover, and descent (for 3 different heights).
- Ascent Method: Ascend to desired height and descend (using 3 different ascent angles).
- Round Trip Straight Flight: Vertical ascent to height, straight flight a designated distance, return to the origin point, and vertical descent (at 2 different speeds).
- Turn Method: Vertical ascent to height, flight in a box-shape with 6 turns. descent. (Using three different turn methods).

For the DJI Matrice 600 Pro, each experiment was performed with four different payloads: no payload (sensors only), 2.5 lbs., 5 lbs., and 10 lbs. For the Tarot 650, each experiment was performed two different payloads: with no payload (sensors only) and 2.5 lbs. payload.

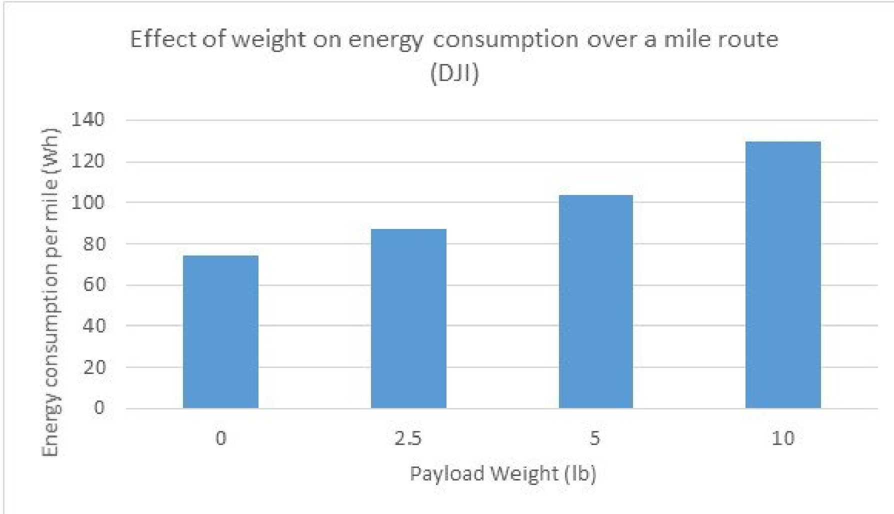

Figure I.1.11.3: Energy consumption for a 1-mile delivery route for the DJI Matrice 600.

Field test results for the DJI 600 Pro showed that payload weight and flight time (determined by speed) has a high impact on drone energy consumption and that the energy consumption for a 10-pound payload is approaching 50% of the energy consumption for a light duty electric vehicle. Figure I.1.11.3 shows the energy consumption versus payload weight for the DJI Matrice 600 Pro. Over a one-mile test route at 200 ft height and 30 mph flight speed, the 2.5 lbs. payload increased energy consumption by 18% over a flight with no payload. Similarly, the 5 lb. and 10 lb. payload tests increased energy consumption by 40% and 75% over the flight with no payload. For the 10 lb. payload flying the mile route, the DJI 600 pro had an energy consumption of about 130 watt-hours. This is a very high energy consumption compared to 200-300 Wh/mi for a light duty electric vehicle which can carry more than 10 times this amount of payload.

The test results from the Tarot 650 drone demonstrated that right-sizing delivery drones could have a significant impact on improving energy consumption. Figure I.1.11.4 shows that the Tarot 650 used approximately 55% less power than the DJI 600 Pro across all the ascend to height tests for an identical 2.5 lb. payload.

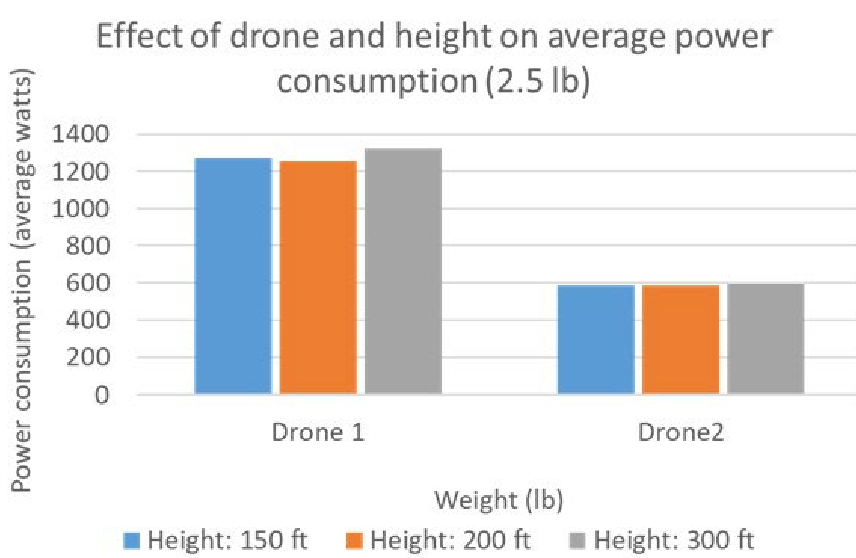

Figure I.1.11.4: Average power consumption for ascending to various heights for the DJI 600 Pro (Drone 1) and Tarot 650 (Drone 2).

Controlled laboratory testing of the drones included total and individual component energy consumption along with direct lift force measurement in various ambient temperatures. Energy consumption was measured using a high accuracy Hioki power analyzer to measure the total battery power output as well as the power consumption of the flight controller and sensors of the drone. The DJI 600 pro was tested at 3 different ambient temperatures: 32, 72, and 95°F. Figure I.1.11.5 show the results for total power consumption versus lift force for the three ambient temperatures.

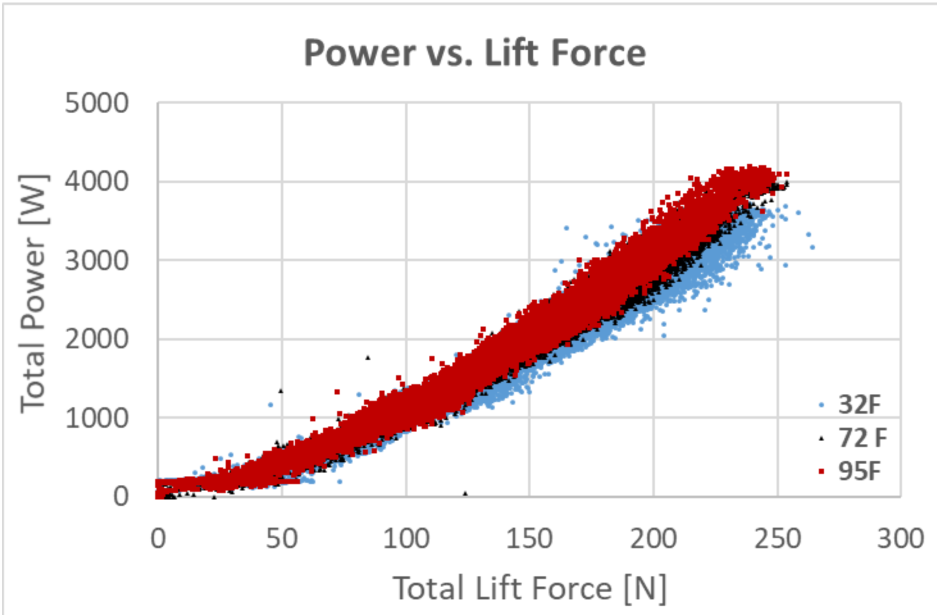

Figure I.1.11.5: Power versus lift force for the DJI Matrice 600 at different temperatures.

Laboratory testing of the Tarot 650 drone in the same conditions as the DJI 600 Pro showed significantly lower power consumption versus payload weight for drone hovering, confirming the ‘in field’ test results. Figure I.1.11.6 shows the hovering power consumption versus payload weight for the DJI 600 and Tarot 650 Drones.

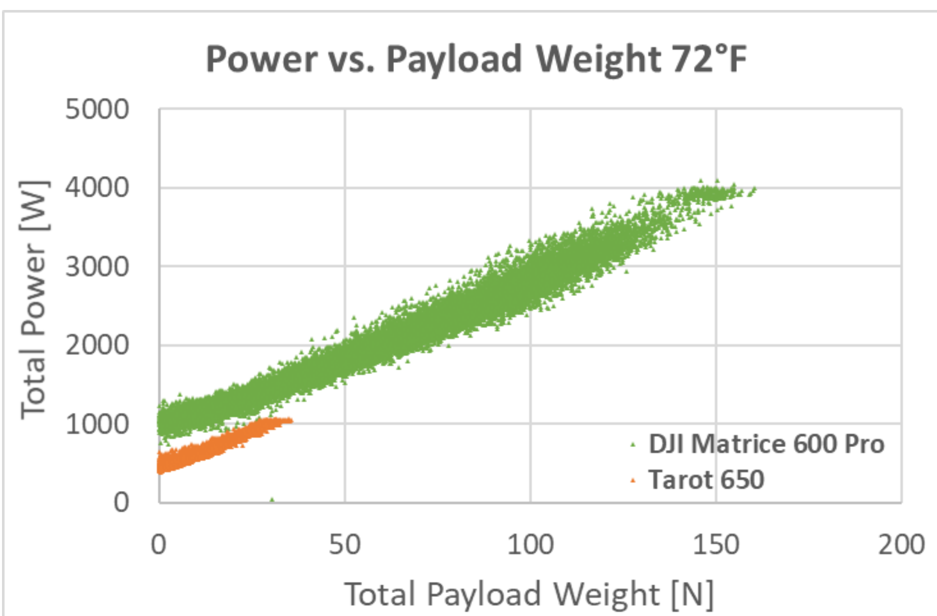

Figure I.1.11.6: Power vs. payload weight for the DJI 600 Pro and Tarat 650 drones.

Additional drone testing and data analysis is ongoing, and the results are being incorporated into models that will be used for optimization.

Conclusions

Initial tests have demonstrated the high value of understanding and optimizing the use of drones for delivery. The methods for deploying a drone can impact overall energy consumption and the total energy can be significant. The tests have shown that weight has a large impact on the power consumption and that right-sizing drones for the payload can have a meaningful impact on the overall energy consumption.

Acknowledgements

Mohamad Roni and Tanveer Bhuiyan from Idaho National Lab have provided valuable expertise in model creation and optimization, and Tanveer has done significant work in data analysis. Matthew Shirk from Idaho National Lab provided sensor platform creation, integration, and maintenance.

The project wishes to thank Heather Croteau from DOE for her ongoing support and feedback. Her input provides consistent improvement and guidance to the work.

I.1.12 Integrated Control of Vehicle Speeds and Traffic Signals for Reducing Congestion and Energy Use (Oak Ridge National Laboratory)

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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 done by drivers, by anticipating what is ahead and decelerating gradually by coasting before arriving at the site where braking would otherwise be required, can provide dramatic fuel savings, and improve traffic flow. Congestion at intersections can be a significant source for such accelerations and decelerations, leading to unnecessary travel delays, increased energy consumption and environmental pollution [2].

ORNL has developed SPaT control strategies that have shown reductions of up to 30% in network average travel delays when compared with those resulting from conventional pretimed 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 for optimal energy savings and traffic flow smoothing. Greater efficiency and mobility benefits can be achieved by integrating the SPaT and speed control and employing connectivity to vehicles.

In this project, we are developing and implementing fully integrated controls for traffic signal timing and vehicle speeds that will be evaluated with connected and automated vehicles (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 vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [3],[5] enabling integration of the traffic signal phase and timing (SPaT) and vehicle speed controls, which have only been evaluated independently in previous studies. Results from this research will help inform decisions for selection of technologies that can yield the greatest energy savings benefits without excessive cost.

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. This information can also be helpful in evaluating the costs of employing either option to achieve a desired performance, for example to decide how many roadside units would be necessary with a direct point-to-point communication system to enable effective speed control functionality along a corridor.

Approach

The project team is conducting detailed traffic simulations for control development, characterizing the performance of the developed strategies, and evaluating a range of scenarios representing different configurations and deployment options. The benefits achieved at different levels of CAV penetration will also be quantified. These evaluations are being conducted in a staged manner, starting with initial development and proof-of-concept via modeling, followed by vehicle-in-the-loop dynamometer testing of a prototype CAV in ORNL's CAVE Laboratory, and finally field evaluations with the systems deployed in the city of Chattanooga. The following is a description of the primary tasks of the project:

Task 1: Controls development and scenario evaluations via simulation (M1–M15): A detailed traffic microscopic simulation model of the test corridor will be employed for 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.

Initial evaluations of the control strategy will be conducted via microscopic traffic simulations and powertrain modeling, and the integrated signal timing and speed control algorithms will be refined in preparation for vehicle dyno testing and on-road evaluation. A range of scenarios will be evaluated to consider different technology options of interest.

Task 2: CAVE Laboratory vehicle dynamometer evaluations (M10–M24): 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. Data transmission range and latency limitations representative of direct point-to-point and cellular communications will be implemented in the simulation to evaluate the system performance under both communications strategies. 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 (M15–M36): 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 describes several key technical accomplishments and results obtained during FY21.

1. Bilinear control algorithm for traffic signal timing control

A bilinear control methodology was developed to calculate signal timings for the current and next cycles of the traffic signals at lighted intersections. For the investigated traffic corridor on Shallowford Road in Chattanooga, there are 8 intersections, and each intersection's green time can affect the performance of the whole system. For each intersection, we have four delay measurements: N-S left, N-S through, E-W left, and E-W through directions. A linearized mathematical control model was developed based on a relationship between the changes of traffic delays and the signal timing inputs, and an optimized timing is determined to minimize the overall delay in the bilinear control model. This model has been implemented in Vissim traffic simulations for the Shallowford corridor. **The approach provides exact timing information for the next complete signal cycle, which is a key enabler for the CAV speed control algorithms**, which use the signal timing to calculate speeds for passage through the intersections during the green light. As shown in Figure I.1.2.1, the delays for the bilinear model are like those for actuated control, and by tuning the model we have achieved lower average overall delays with the bilinear control (21.7 seconds) than for actuated control (24.4 seconds).

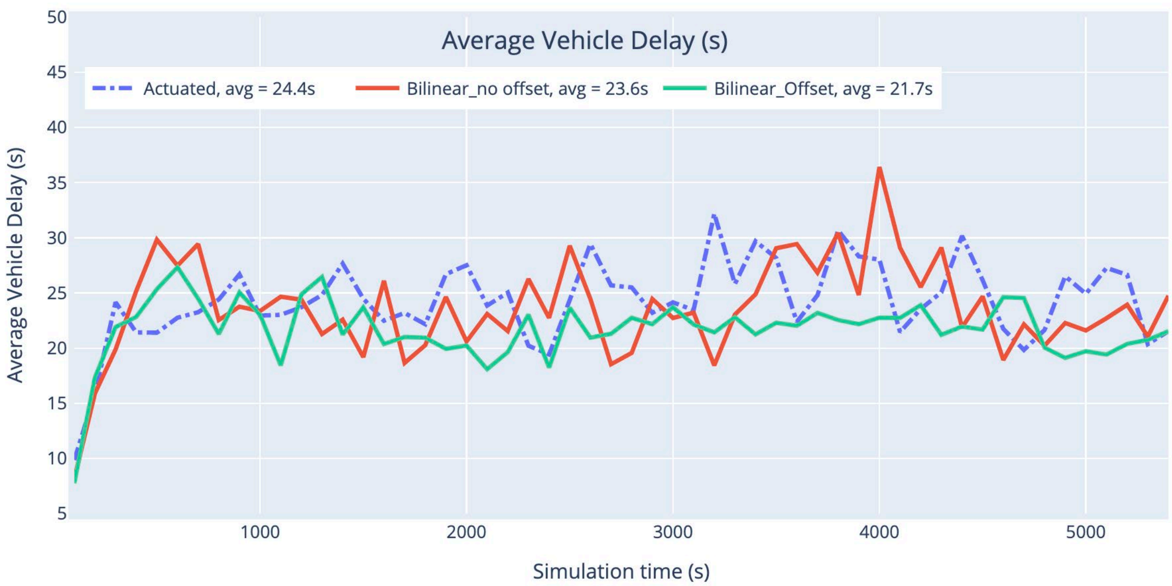


Figure I.1.12.1 Delay comparisons between different signal control models.

2. Green wave speed control algorithm, and integration with signal timing control

The green wave speed control algorithm employs a basic model for calculating desired speeds based on knowledge of the temporal window of the current/upcoming green light and the locations of connected and automated vehicles (CAVs). This algorithm is meant to serve as a simple approach appropriate for centralized control that can be used to determine a target speed for CAVs without detailed knowledge of surrounding traffic conditions or individual vehicle characteristics. As shown in Figure I.1.1.2, given the location of the CAV and the green light windows, the target speed, v_{target}, is determined based on Eq. 1.

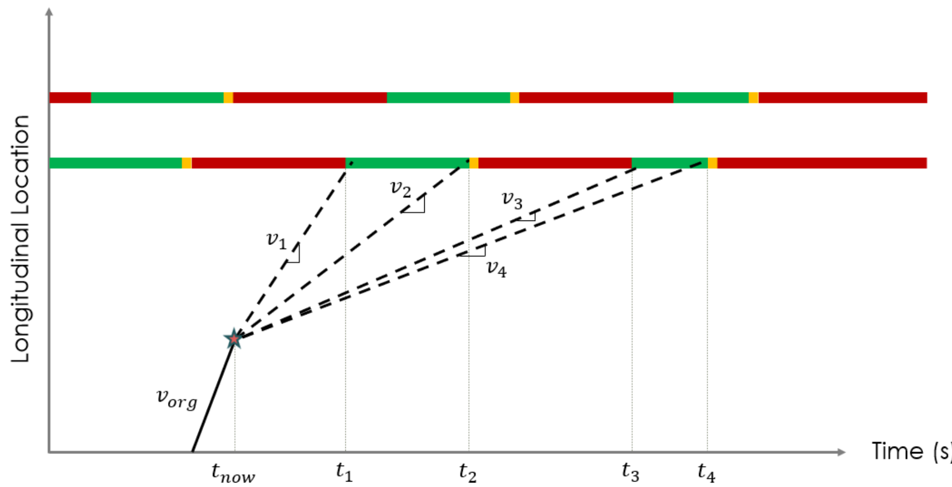
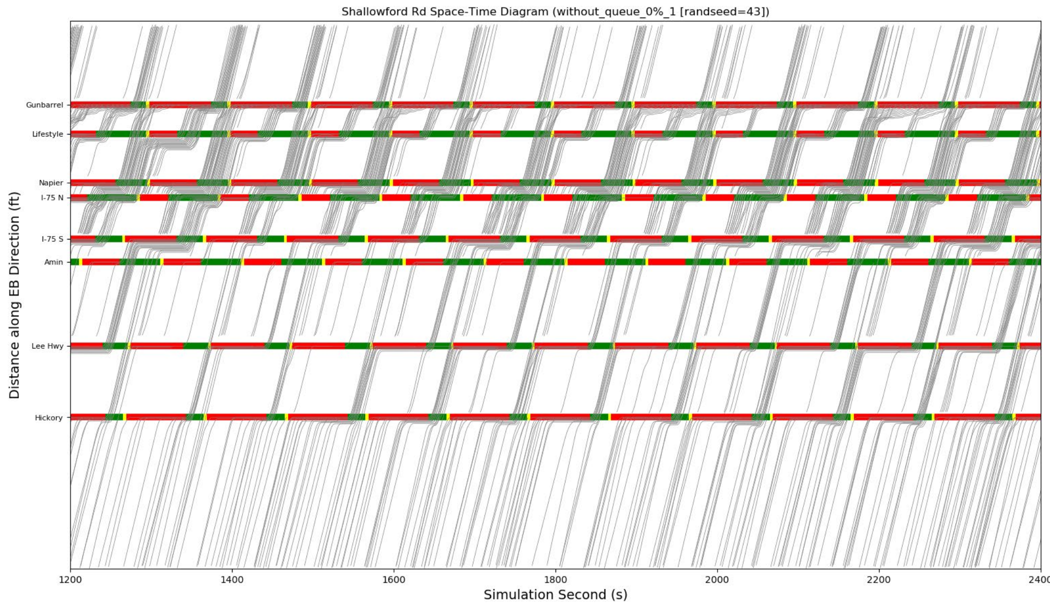


Figure I.1.12.2 Illustration of green wave speed control algorithm and potential ranges of speed given distance from CAV to the next intersection and the green phase time periods.

$$v_{target} = \begin{cases} v_{orig} & , v_2 < v_{orig} \le v_1 \\ v_3 & , v_3 < v_{orig} \le v_2 \\ v_{orig} & , v_4 < v_{orig} \le v_3 \\ v_{orig} & , v_{orig} \le v_4 \end{cases} \quad (1)$$

Figure I.1.12.3 shows the vehicle trajectories from a Vissim simulation with and without the speed control algorithm. The modified speed profiles of the CAVs (shown in blue) in Figure I.1.12.3(b) leads to considerably less braking, and stops are completely avoided at many of the intersections. To avoid excessively low speeds, the speed control is not engaged at some intersections, but it may be possible to improve signal coordination to reduce these stops. Nonetheless, the speed control algorithm yields significant reductions in braking, and thus to reduced fuel consumption for the CAVs.

(a)



(b)

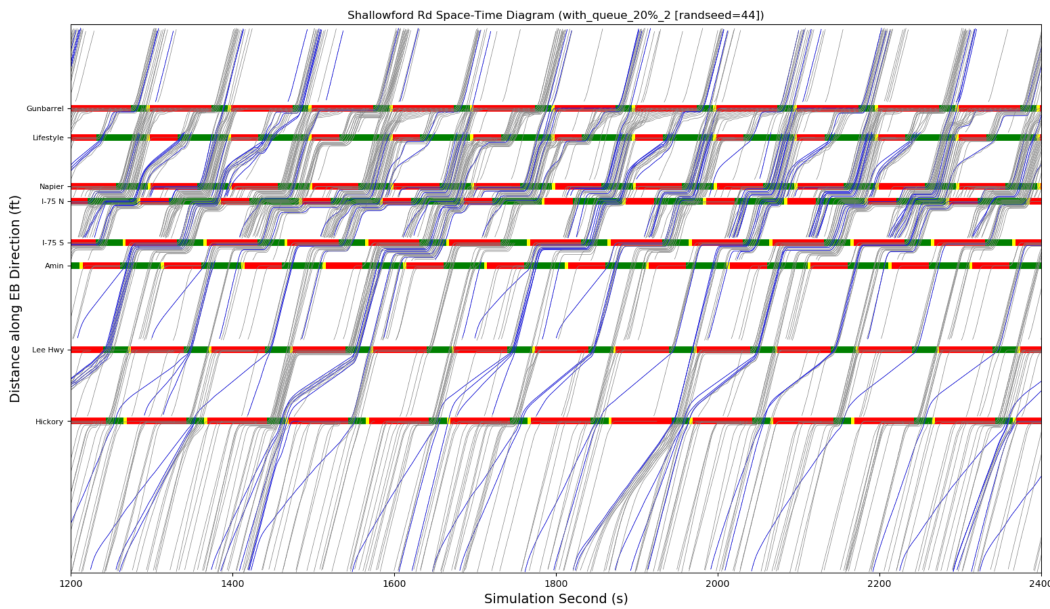
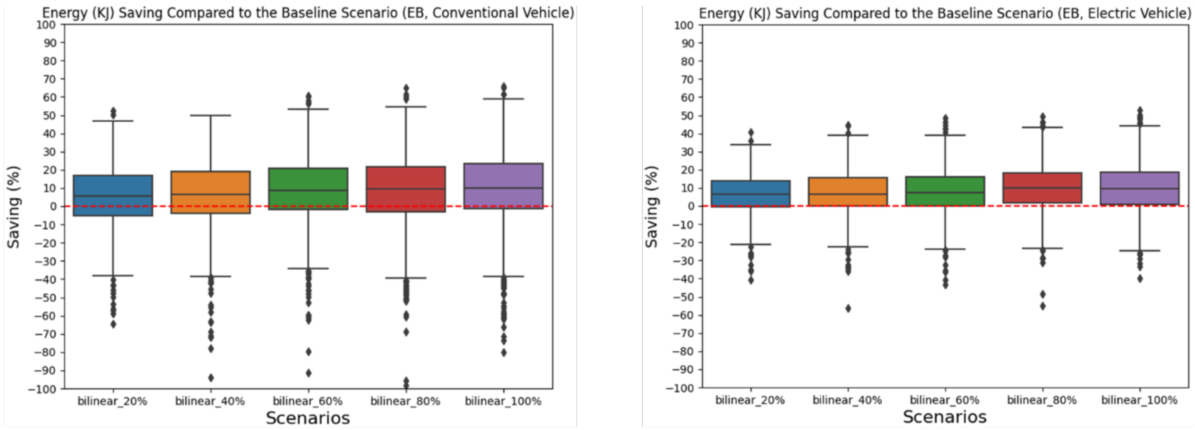


Figure I.1.12.3 Space-Time diagrams showing vehicle trajectories (a) without green wave control; and (b) with 20% of vehicles being controlled by the green wave algorithm.

The green wave speed control and signal timing control algorithms were integrated in the Vissim simulations and energy savings were evaluated. A route-based energy consumption evaluation was conducted using vehicle pairs identified between the baseline scenario (i.e., bilinear signal control without speed control) and five scenarios corresponding to different levels of CAV penetration (20%, 40%, 60%, 80%, and 100% CAVs). These comparisons are made between vehicles (CAV vs. non-CAV) that traveled the same route and entered the network at the same time (within 5 seconds) to ensure similar traffic conditions were experienced in both scenarios in the CAV and non-CAV cases. Figure I.1.12.4 shows the energy savings for the different CAV scenarios in the eastbound (EB) direction on Shallowford Road for conventional vehicles (left figure) and electric vehicles (right figure), respectively. The results indicate that there are significant energy savings for the CAVs in the integrated control scenarios, regardless of the levels of CAV penetration and vehicle types. Higher levels of CAVs penetration generally yield greater energy savings, and the 100% CAVs penetration level has the highest energy saving (11.05% for conventional vehicles and 11.46% for electric vehicles).



Average Route-Based Energy Saving Compared to Baseline Scenario (Conventional Vehicle)					
Scenario	20% CAV	40% CAV	60% CAV	80% CAV	100% CAV
Savings	7.68%	8.25%	10.26%	10.22%	11.05%

Average Route-Based Energy Saving Compared to Baseline Scenario (Electric Vehicle)					
Scenario	20% CAV	40% CAV	60% CAV	80% CAV	100% CAV
Savings	8.18%	8.49%	9.63%	11.56%	11.46%

Figure I.1.12.4 Box plots showing route-based energy savings for the integrated control strategy relative to a scenario without speed control. The left figure gives the energy saving for conventional powertrain vehicles, while the right figure is for electric vehicles (regenerative braking included).

Conclusions

The ORNL team has made excellent progress in developing the control algorithms and methods for implementation of integrated vehicle speed and signal timing control algorithms. Model results using a simple green wave speed approach have shown energy savings exceeding 10% for CAVs, and further improvements are expected with refinements of the model to account for queue formation and dissipation in the speed control algorithm, as well as planned improvements for the signal control that will include some of the beneficial features of actuated control but without a negative impact on the energy consumption. The team has also developed and demonstrated an effective data management strategy for cloud-based communications to CAVs that is highly scalable. The work in the first year of the project has focused on controls development and modeling, but we will be moving forward with implementation of the control strategies in a prototype CAV test vehicle and will conduct dynamometer evaluations of the integrated control strategy in FY22.

Key Publications

1. Xu, H., C. Wang, A. Berres, T.J. LaClair, J. Sanyal. "Interactive Web Application for Traffic Simulation Data Management and Visualization" *Transp. Res. Rec.* 2021:1–19 (August 2021). https://doi.org/10.1177/03611981211035760.

2. Berres, A.S., T.J. LaClair, C. Wang, H. Xu, S. Ravulaparthy, A. Todd. "Multiscale and Multivariate Transportation System Visualization for Shopping District Traffic and Regional Traffic" *Transp. Res. Rec.* 2675(6): 23–37 (2021). https://doi.org/10.1177/0361198120970526.

3. LaClair, T., R. Wang, J. Yuan, H. Wang, W. Li. "Milestone Report: Speed Control Algorithm for "Green Wave" Approach (For SMART Mobility Project: Integrated Control of Vehicle Speeds and Traffic Signals for Reducing Congestion and Energy Use)" ORNL/TM-2021/2146, Oak Ridge National Laboratory (2021).

4. Xu, H., Berres, A., Wang, C.R., LaClair, T.J., Sanyal J., "Visualizing Vehicle Acceleration and Braking Energy at Intersections along a Major Traffic Corridor," *Proceedings of the Twelfth ACM International Conference on Future Energy Systems*, 401–405 (June 2021). https://doi.org/10.1145/3447555.3466603.

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2. Wang, H., M. Zhu, W. Hong, C. Wang, G. Tao, and Y. Wang. "Optimizing Signal Timing Control for Large Urban Traffic Networks Using an Adaptive Linear Quadratic Regulator Control Strategy," *IEEE trans Intelligent Transportation Systems* 2020:1–11 (August 2020). https://doi.org/10.1109/TITS.2020.3010725.

3. LaClair, T.J., Z. Gao, C. Wang, J. Rios-Torres, et al. "Development of a Real-Time Mobility Control and Visualization System with Predictive Vehicle Speed Control for Connected and Automated Vehicles (CAVs)," *32nd International Electric Vehicle Symposium (EVS32)*, Lyon, France (May 2019).

4. Gao, Z., T. LaClair, S. Ou, et al. "Evaluation of electric vehicle component performance over eco-driving cycles," *Energy* 172: 823–839 (2019). https://doi.org/10.1016/j.energy.2019.02.017.

5. Xu, H., C. Wang, A. Berres, T.J. LaClair, J. Sanyal. "Interactive Web Application for Traffic Simulation Data Management and Visualization" *Transportation Research Record* 2021:1–19 (2021). https://doi.org/10.1177/03611981211035760.

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I.2 Artificial Intelligence, High-Performance Computing, and Data Analysis

I.2.1 Big Data System for Mobility Phase 2

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Start Date: January 1, 2021
End Date: December 31, 2022
Project Funding: $4,000,000
DOE share: $4,000,000
Non-DOE Share: $0

Project Introduction

This project is focused on using data science and DOE National Laboratory high-performance computing (HPC) 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 are taking a data driven approach: implementing large-scale machine learning/deep learning (ML/DL) methods for high-value applications as well as integrating real-world data into Artificial Intelligence (AI)-enabled, high-speed, urban-scale transportation network parallel-discrete event simulations (PDES). Our focus is 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.

Objectives

This project extends and improves an integrated data analytics platform that can be used for solving transportation problems at scale. A core focus is to use AI to build models that can be transferred to organizations that do not have access to HPC resources. Our objective is to allow practitioners to run high-value scenarios of complex transportation solutions and develop next-generation planning and control solutions for transportation impacts in cities.

Specifically, we use AI techniques to:

- Ingest and condition large scale transportation related datasets for the purpose of improving the underlying travel demand models and the dynamic models that are embedded in the simulated transportation response model. This includes using neural networks to codify signal dynamics on arterials and inferring the signal phase and timing for arterials with congestive flows from global positioning system (GPS) traces.
- Improve the previously developed Diffusion Convolution Recurrent Neural Network (DCRNN) model of traffic dynamics for the purpose of integrating it into large scale simulations and using it as a mechanism to remediate impacts of congestion. This includes developing uncertainty estimates of the predicted traffic flows and speeds so that consequent actions for control can consider uncertainty, extending the model to ingest large scale GPS data so that predictions can extend to larger arterials,

and investigate the extent to which transfer learning can then allow this model to geolocations in which large scale data sets are sparse.

- Extend the platform to allow practitioners to evaluate and validate the outcome of scenarios of interest to their city/business. This includes going beyond the ML/DL approach which codifies correlation to applying causal inference so that practitioners are provided the underlying reasoning behind the outcomes, determining if the computational models can be transferred from HPC to the cloud while still maintaining the computational efficiencies, and developing surrogate models from the large data sets that can be generated using HPC resources.
- Improve existing computational techniques to investigate congestion mitigation solutions. This includes using the predictive capability of the DCRNN to detect and respond to events, creating a large-scale control response model that includes communication latency to capture next-generation implementations of traffic control solutions, investigating the impact of reinforcement learning for signal control on large scale arterials, and including energy impacts of these potential improved control solutions.
- Develop advanced analytics for evaluating city level impacts of control solutions.

Results

Task 1: Data Ingestion and Conditioning (LBNL; NREL

Data Sourcing

Mobility Data: A key element of this project is its emphasis on being data driven. To this end, we use sourced mobility data [1] for determining the location of traffic signals and improving our travel demand model to reflect more current information. The Mobiliti simulation travel times are also validated with the mobility data. We have implemented many improvements and additions to the mobility data processing pipeline. Because real-world trajectories do not always reflect point-to-point travel, a mechanism for filtering mobility data for point-to-point travel is being developed to remove outlier trajectories that are not appropriate for validation purposes.

Our processing has been migrated to the AWS cloud to facilitate large scale data processing. We unfortunately suffered a server failure and lost our localized processing capabilities.

LBNL successfully completed a negotiation with Wejo to conduct a data evaluation and subsequent purchase of the data. The data has been delivered to our AWS S3 environment and will provide a basis for future analytics. Our data evaluation of Wejo data focused on data quality and usefulness to the project. The purchase has been completed for one month of movement data for a selection of weeks that would likely have interesting dynamics. NREL has procured similar Wejo data from California and New York which will allow us to collaborate closely using the same data foundation.

Additional Transportation Network Data: The University of California Partners for Advanced Transportation Technologies (PATH) Connected Corridors project was cancelled by Caltrans. We had planned to access traffic signal information when the system was operational; as a backup plan we archived approximately 4 months of the data. We reconfigured the databases to reduce hosting costs by 87%, which will save over $4000 annually. These are stored in a MongoDB database and will provide additional real-world baselines for our traffic signal control investigations in the future.

Improved Demand Modeling

Activity-based travel demand models are composed of day-of chained trips for vehicles/households. Each trip is associated with a certain purpose which is related to the activity type performed at the destination of the trip, e.g., work trip: Origin -> home and Destination -> work. This type of data must be organized and cleaned to develop GPS traces that define the device path over time. From cleaned GPS traces, we detect stay points in the traces. Stay points are the locations where the traveler slows/stops to perform an activity. We implement stay point detection algorithms and detect staypoint locations with the metrics of moving speed, minimum stay duration and maximum moving distance. By splitting traces into subtraces, where each subtrace represents a single trip, we get information that can further inform our travel demand model.

The trip purpose is a key feature for travel demand estimation. Given that probe data has no demographic information or manually tagged information, we infer trip purpose from the features of the trace, e.g., activity start time, stay duration, land use in the vicinity of the destination. We investigated the use of machine learning algorithms to classify trip purposes by comparing logistic regression, support vector machine, neural network and random forest models. Through this analysis, we determined that a tree-based classification model performs best. The next step is to determine the optimal mechanism for adjusting the travel demand profile and integrating the new model into the Bay Area model. In addition, we recently acquired connected car generated datasets, enabling evaluation of differences between probe generated and connected car datasets to ensure that source data biases are considered.

Task 2: Deep Learning Models from Field Data (ANL; LBNL)

A data preprocessing and curation pipeline has been developed that processes traffic sensor data, specifically inductive loop data in freeways, to generate high-quality training data by leveraging associated labeling functions, which can be domain knowledge-related or simple heuristic rules.

Uncertainty Quantification in DCRNN Models

An ensemble of recurrent neural network models were developed to classify traffic incident signals with uncertainty estimation. A key element of the approach is to separate the two sources of uncertainty: aleatoric and epistemic uncertainty as this is important for proactive traffic management. We demonstrated that the uncertainty quantification (UQ) estimation techniques developed work well for large scale networks. The uncertainty measures were associated with Traffic Dynamic/Coefficient of Variation analysis and led to a suggested way to use the measure for improving our models. We then developed an online real-time incident detection approach that leverages the model ensemble and the uncertainty to detect incidents. This weak supervised learning approach had a significant impact on the model performance.

TL-DCRNN Development

Our TL-DCRNN model was improved and tested on a variety of regions. We demonstrated improved forecasts for the Los Angeles region using a network trained on Bay Area data. This indicates are that our models are codifying the dynamics on these types of network constraints and can likely be transferred to other regions. Our current work has focused on the entire highway network in the State of California. The next step for this effort is to determine if real-time GPS data can be a proxy for the inductive loop sensor data that currently is used for developing predictive models for highway traffic dynamics.

Task 3: Surrogate Models and XAI from DL Models (LBNL; ANL)

Surrogate Models

The success of building surrogate models for complex systems such as ours requires significant amounts of training data. The training data for our model will be created using Mobiliti. However, because we wish to codify the dynamics of the network we will need to understand how to design the input data for generating training data that will innervate the entire road network. The design of training data generation is currently under development. As a first step, we conducted an experiment similar to our previous work that used Caltrans Performance Measurement System (PEMS) highway sensors but now using Mobiliti-generated data at the PEMS sensor locations. We identified “sensors” in the Mobiliti network that match PEMS sensor locations, and this approach will generalize to other subgraphs of the whole network, so that we can partition the network and train and run inference on each partition. Routes over the full network were then processed to generate origin and destinations (O/Ds) pairs and paths on the subgraph of interest.

Mobiliti Simulator

Improvements to the Mobiliti simulator included: Addition of fleet/truck data from SFTA along with parameters to control mode / purpose selection for O/D demand matrix inputs; more efficient routing methods; improvements to our core vehicle controllers (dynamic rerouter) logging that generates reroute and divert events, captures times, leg and link identifications (IDs), congested trip estimates, and old and new routes for each reroute event; parameterized thresholds for deciding when vehicles should reroute. Analytics for evaluating the improvements included parameter sensitivity sweeps to illustrate how the system responds to changing dynamic rerouting parameters.

With regional control being an important focus of this phase of the project, we augmented Mobiliti to include signal level control—(see Task 4). This required a major enhancement of our link timing model to support dynamic signal timing. A dynamic signal controller mechanism and interface in Mobiliti was developed to change the signal timing (cyclic or acyclic control, cycle duration, phases, green durations, etc.) for link-to-link transitions. Link actors now delay sending enqueue requests downstream until signal timing is agreed upon by the controller. New input files specify initial signal timings and signal controller parameters and link subscriptions. At initialization, signal controllers register which 1) links to receive updates from, 2) properties they need (e.g., queue length, flow, speed), and 3) thresholds to use to control the frequency of updates. Links register the subscribed properties, track them whenever they advance their state, and send updates as needed to subscribed controllers. Controllers periodically execute their model to determine new signal timing parameters and send updates to corresponding links. Finally, a controller interface was co-designed with Task 4 members to allow new controller types to be easily plugged into Mobiliti.

Task 4: Congestion Mitigation Solutions (LBNL; ANL; NREL; Siemens)

Reinforcement Learning (RL) for Traffic Optimization

Regional control using signal optimization was investigated by developing a process for improving traffic flow and reducing energy consumption/emissions by dynamically adjusting traffic light durations and finding alternative routes. These algorithms will plug into the dynamic signal controller design in Mobiliti.

Working toward the goal of turning on a baseline signal control function in Mobiliti we have used real-world GPS data to identify the location of signals, identified maneuvers/link sequences for the intersections, mapped the maneuvers to signal phases, and used demand and supply to identify the required signal timing. This resulted in an input file for Mobiliti that assigns green time to each phase for each hour for over 81K locations in the network.

Incident Detection on Highways

Developed real-time traffic incident detection using a data-centric machine-learning workflow. Data curation of incident reporting improved the results of our classifiers significantly to an initial detection rate of 90%, with a false alarm rate of 8%. Based on our understanding of the reporting quality issues, the approach was improved further to include label automation that yielded a detection rate of 96% and false alarm rate of 12%. This model will be presented to a state Department of Transportation for potential integration into a traffic management center with the goal of improving incident response times.

System-Level Methods for Improved Energy Estimation

Currently, the Mobiliti simulation has three fuel use models that are randomly distributed across the population of drivers. Meaning the models are associated with individuals and are then applied to all trips for the individual. The three models, generated by dynamometer testing at Argonne, are a Nissan Altima, a Ford Fusion and a Ford F-150. They are distributed as 40%, 40% and 20% of the population respectively.

To understand the impact/sensitivity of the fuel modeling we have compared the initial Mobiliti energy models with estimates from NREL RouteE-powertrain models for similar vehicle types using randomly selected Mobiliti vehicle trips. In preliminary comparisons, aggregate RouteE-powertrain estimates have shown better agreement with expected average fuel economies across a region. One immediate improvement is that the initial three-vehicle fuel mapping approach does not account for the impact of road grade on energy consumption, while RouteE-powertrain does. RouteE is well validated against higher fidelity powertrain simulation and vehicle-reported on-road fuel consumption data. Use of the RouteE approach additionally enables a wider range of vehicle powertrain types (such as hybrids and electric vehicles) to be included in the simulations. NREL makes RouteE-powertrain estimates available publicly through a web application programming interface (API), but to improve computational performance, local versions of RouteE energy consumption rate "lookup" tables are being provided for Mobiliti energy calculations.

As a key focus of the project is to be data driven, we are using the GPS trajectory data from the Data Sourcing task to determine how energy consumption modeling can accurately capture the real-world dynamics of driving in congested urban environments. Explicit representation of vehicle start/stop dynamics had been missing from the initial Mobiliti energy modeling and can have a substantial impact on real-world energy consumption. To characterize the real-world dynamics of urban driving, Wejo drive cycles are being analyzed over individual road links in San Francisco. The drive cycles, combined with powertrain simulation using NREL's FASTSim software, are being used to quantify the energy impacts of stops at traffic signals and slowing or stopping due to congestion—both of which can be extracted from Mobiliti simulations. Additionally, the real-world trajectories are being used to quantify the variance and stochasticity of driving behavior on individual links and paths in the road network—thus capturing the variation in energy consumption. In the second year of the project, actual on-road data energy consumption data will be used to validate the model predictions.

A long-term vision for the Mobiliti platform is to use it as a digital twin for a region. To be implemented in a real-world environment, the communication infrastructure will be important to consider if real-time decision making is required. For this purpose, we are evaluating the latency for current and emerging Internet Technology infrastructure. We have defined the physical information and communication technology (ICT) infrastructure and its performance / capabilities, categorized distributed algorithms based on communication patterns and mapped those patterns to our ICT infrastructure. Our next step is to create a model of the ICT infrastructure to include in the Mobiliti simulation.

Communication Patterns

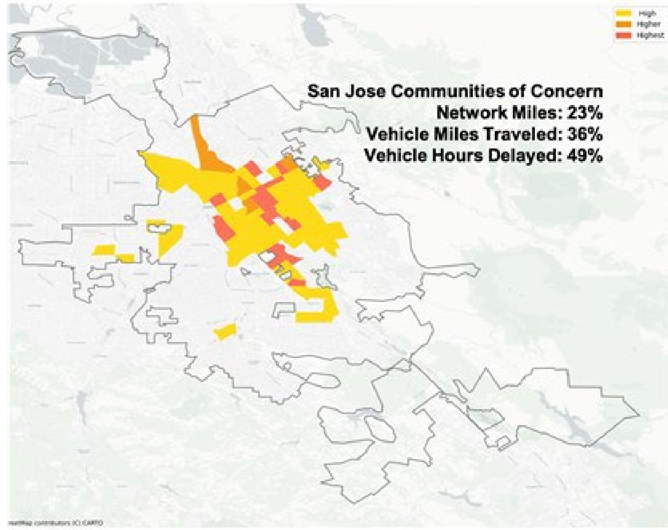
To model the communication patterns, we reviewed the communication patterns of current signal controllers and reviewed Smart City infrastructure patterns in the US. We identified that various factors, including the multiple vendors, cities, and local administrations has forced cloud synchronization. Synchronization is hard to perform at mobile edge cloud (MEC), but we see it a future development from key hardware vendors. We also reviewed communication developments associated with connected vehicles and 5G and produced a definition of a virtual intersection with traffic flow algorithm metrics that could be derived directly from observed traffic patterns and inferred from nearby sensors / intersections.

Baselining Traffic Environment Scenarios

While our focus is on next-generation traffic signal control, we have also reviewed current control methods that are used in industry so that we have a foundational understanding of the pros and cons to alternative methods. In particular, we reviewed the following approaches: split, cycle and offset optimization technique (SCOOT); Sydney Coordinated Adaptive traffic (SCAT) system; urban traffic control system (UTCS); optimization policies for adaptive control (OPAC) system; real-time traffic adaptive signal control system (RHODES); and the Markov Decision Process (MDP). We generated hourly baseline traffic signal timings as inputs for Mobiliti using simulated traffic flow data by a traffic engineering approach.

Task 5: Stakeholder Engagement (LBNL)

The City of San Jose is building a Decision Support System (DSS) for their planning division. The results from Mobiliti will be integrated into the platform so that the planners have direct access to the data. Key metrics defined through our data analytics processing are being assessed for evaluation as Key Performance Indicators (KPIs). The metrics are evaluated for optimized traffic assignments such at User Equilibrium - Travel Time and System Level Equilibrium - Travel Time. These various routing approaches have impacts on communities is various ways on schools and disadvantaged groups and we have applied these methods to quantify impacts for all of the cities in Bay Area.



Because Mobiliti provides a regional transportation simulation, cities other than San Jose are captured in the simulated environment. To increase stakeholder engagement, we developed an automated web-based report pipeline for generating metric reports for cities and counties in the Bay Area. The reports, found at https://smartcities.berkeley.edu/mobiliti-reports/ include advanced analytics based on link reclassification, equity indicators and truck traffic estimates. For San Jose, existing bike infrastructure access and equity analysis was also included.

The figure on the right, found in the San Jose Mobiliti report, demonstrates transportation related impacts on Communities of Concern. **While these low-income communities account for only 23% of the network miles in the city, they bear the impact of 36% of the city's vehicle miles travelled and experience 49% of the delay.** This translates directly into health issues associated with emissions, safety and livability issues because of high average daily traffic in their neighborhoods, and lifestyle impacts associated with the mobility challenges in these lower income communities. San Jose is dedicated to reducing vehicle use and improving transit solutions for all their constituents in their Access & Mobility Plan.

Validation

The Mobiliti road network is continuing to be modified to align with alternate sources of information. In particular, highway free speeds were adjusted to reflect values close to Caltrans PEMS data and validated with other networks that are often used for Bay Area simulation.

Collaborations

Additional collaborations included providing simulation results for analyzing Tokyo network model with UC Berkeley researchers focused on evacuation planning. This provides our team additional validation results as we compare our results with their existing methods that currently require several days of computational time.

Conclusions

Key progress this year focused on improvements to the Mobiliti platform to increase the fidelity of the simulation, including integration of predictive Deep Learning for improved understanding of traffic dynamics, dynamic routing improvements to generate more realistic representations of urban movements, and adding signal control to simulate congestion patterns on arterials. Signal control algorithms can now be investigated as a mechanism to improve traffic movements beyond typical corridor controls. New demand models that include fleet/truck data from SFTA were created and real-world, data from probes and connected car data were investigated as a mechanism to update the foundational demand SFTA demand models making the platform reflect more realistic urban mobility needs. The City of San Jose continues to be a close collaborator and provides feedback to ensure relevance of the project to future urban transportation solutions. The results of Mobiliti simulations are presented as Bay Area city reports and include equity metrics for evaluating the transportation dynamics and its related congestion as experienced by lower income communities.

Key Publications

1. Uncertainty Quantification in Spatiotemporal Graph Neural Networks for Short-Term Traffic Forecasting, T. Mallick, P. Balaprakash and J. Macfarlane.

2. Data-centric supervised learning workflow for highway traffic incident detection, Y. Sun, P. Balaprakash, T. Mallick, and J. Macfarlane. Submitted to ACML 2021

3. Highway traffic incident detection with multi-task weak supervision, Y. Sun, P. Balaprakash, T. Mallick, and J. Macfarlane.

4. Cy Chan, Anu Kuncheria, Bingyu Zhao, Theophile Cabannes, Alexander Keimer, Bin Wang, Alexandre Bayen, and Jane Macfarlane. "Quasi-Dynamic Traffic Assignment using High-Performance Computing." Submitted to Transportation Research Part B: Methodological.

References

1. Mobility data is data collected from mobile devices that generally include device id, time stamp, (latitude, longitude), speed and heading.

I.2.2 Scaling up the Real-Time Data, Simulation & AI, and Control for Optimizing Regional Mobility in the United States (ORNL, NREL)

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Start Date: January 1, 2021 End Date: December 30, 2022
Project Funding: $4,000,000 DOE share: $4,000,000 Non-DOE share: $0

Project Introduction

CTwin research has delivered a regional-scale, open, scalable, real-time situational awareness platform that brings in 500+ primary data streams from 7 proprietary vendor systems across 3 institutions, in addition to 40+ distinct data layers to create a capability that is unique for the Vehicle Technologies Office (VTO). Metrics based on industry standards (MAP-21, Automated Traffic Signal Performance Measures - ATSPM) 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 have produced novel and exceptionally well received data visualizations. Data-driven discoveries have led to an implementation of a Model Predictive Control (MPC) based on an 18% energy savings estimate that realized more than 16% energy savings in the field (Figure I.2.2.2).

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

The goal of the current research is to employ Artificial Intelligence (AI) and High-Performance Computing (HPC) methods to scale up the Chattanooga Digital Twin, CTwin. CTwin will have increased geographical and computational scale. The objective is to accomplish 20%+ energy savings across city streets and freeways for passenger traffic, freight, and connected vehicles (CV) (Figure I.2.2.1). The research will deliver:

a. Inter-regional geospatial situational awareness with real-time data feeds from transportation departments of Tennessee, Georgia, and City of Chattanooga, fused with real-time CV feeds from Waze, FreightWaves, TomTom, and other partners.

b. 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 the detection of sensor anomalies.

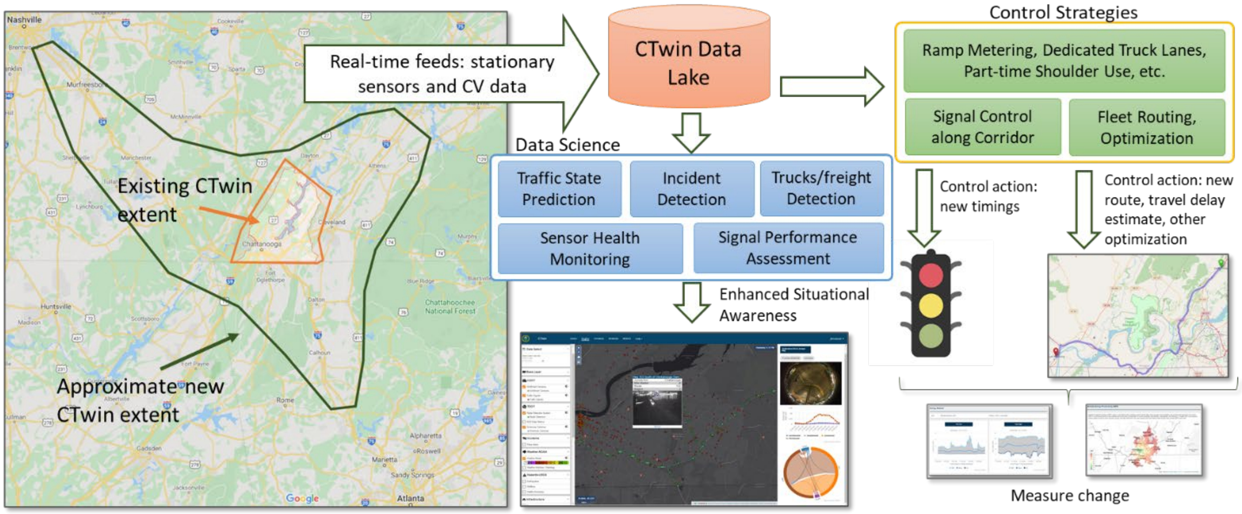

Figure I.2.2.1 Illustrative schematic for the inter-regional CTwin highlighting the various component technologies and innovations.

c. Leapfrog the existing single corridor control strategy to obtain an integrated regional mobility control solution using AI that encompasses the interstate and adjacent principal roads for the evaluation of signal control strategies and other optimization options for connected fleets/vehicles.

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.

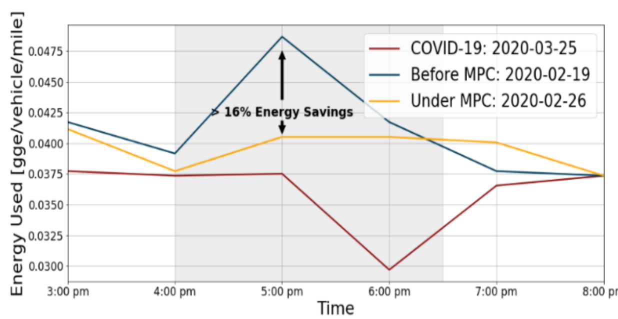

Figure I.2.2.2: Energy Savings on section of SB I-75 on Shallowford Rd

Objectives

Congestion continues to be a significant contributor to energy inefficiency in the US. In 2017, highway congestion wasted over 3.3 billion gallons of fuel and caused 8.8 billion hours of lost productivity. Trucks accounted for $20 billion (11%) of the cost representing 7% of traffic. Prior research has shown that situational awareness combined with adaptive traffic controls, including a small percentage of CVs, can significantly reduce congestion and improve traffic flow leading to savings of energy and time, and improvement in productivity. Research groups have made significant strides in using HPC and AI towards developing vehicular traffic situational awareness.

CTwin 2.0 builds up on the success of the previous work towards two key objectives:

a. Scaling up the situational awareness capabilities to interface with Georgia DOT systems and integrating data feeds from TDOT's newly deployed advanced sensing infrastructure.

b. Employing AI and HPC to expand and scale up the modeling and control strategies, the algorithms, and the implementation mechanisms towards an integrated regional mobility capability comprising a section of the interstate and nearby primary roads.

Approach

This section elaborates upon the project approach, specific tasks to be accomplished, and the technological barriers being addressed.

a. Expanded inter-regional area for real-time and predicted situational awareness:
   i. Expanding to inter-regional scale of situational awareness.
   ii. Calculating system performance measures for mobility at multiple geospatial scales.

b. Data science and AI for signal performance, incident detection, freight detection, sensor health, and energy estimation:
   i. Scaled up signal performance assessment for the region.
   ii. Real-time incident detection within 30 to 120 seconds of the occurrence in contrast to the 911 call which, on average, is 12 minutes after an incident.
   iii. Real-time truck movement detection from 100+ streaming traffic camera footage to build a picture of truck/freight flow through the region.
   iv. Improving volume and energy estimates using Gaussian Process or Bayesian based ML models to predict near-future traffic volumes including presence of delays models for energy prediction.

c. Inter-regional modeling and simulation for energy optimization:
   i. Extend simulation into Georgia for simulated baseline performance.
   ii. Evaluate and vet AI-based traffic control in simulation using HPC.

d. Scale up the control strategy, algorithms, and mechanisms of implementation:
   i. Develop implementation of AI-based signal control methods.
   ii. Deploy signal control for integrated regional scale mobility.
   iii. Optimize and enhance connected freight and fleet operations.

Results

FY21Q1 Summary: AOP creation and awaited funds to start work

FY21Q2 Summary: The CTwin 2.0 Project split the deliverables into 4 categories for easier tracking and more manageable tasks of work. These include Situational Awareness (SA), Data Science (DS), Modeling and Simulation (MS), and Control Physical (CP). These categories are distinct in which the project team, and partners, can discern the activities towards a detailed project management plan. Furthermore, a Jira board was set up to internally monitor the status of the project more closely and allow a more unified reporting structure of work completed. A monthly sponsor check has given the prospect to ask questions and obtain clarification(s) of unknowns and/or areas of opportunity as well as communicate interim successes and project risks. An updated project AOP was submitted to increase its visibility and understanding the project with its expectations. Work started in FY21Q2 on all fronts, i.e., situational awareness, data science, modeling and simulation, and cyber-physical control.

FY21Q3 Summary: A cyber-physical control experiment was run at a time of day along Shallowford Road. Areas in downtown have been identified for future experiments. The Gridsmart and Smartway real time feed ingestion bugs were fixed in time for the experiments. The RDS feeds which ingests historic data has several missing data pertaining to the geographical ids and some of the data fields have also changed since last year. Further, we are also looking into the performance aspects of the RDS ingestion on to existing database. We also addressed a web interface vulnerability, and the relevant code was pushed both to develop and production branch. We continuously worked with the previous developers and IT operational team to fix the essential services and ensure they were up and running.

FY21Q4 Summary: In this quarter, a 24x7 cyber-physical field experiment on Shallowford Rd was conducted over a 3-week period. Monitoring and alerting capabilities were built for unmonitored execution. An invention disclosure for near real-time incident detection was filed. The SUMO NEMA controller code that was developed by the team was requested to be contributed to the SUMO codebase. Various other cyber-security vulnerabilities were fixed. The next generation data lake was also conceptualized. A complete assessment of the scale up of control strategy was developed.

We now describe the for thematic areas in more detail:

Situational Awareness:

With the addition of partners and the changes in IT infrastructure in several partner organizations, the ingestion of various data sources experienced some issues and maintenance tasks were initiated to address these. Regarding system performance, the approach and feasibility of consistently computing the various metrics across efforts at NREL and ORNL is finalized. These include mobility, energy, safety, and MEP metrics across different scales of intersection, corridor, and regional levels. We have also received the road network/geometry data, historical data up and have a methodology for ingesting the data in real-time from GDOT.

The Chattanooga Public Works (CPW) relationship went into silence. Covenant transport made a business decision to extract themselves as the COVID pandemic forced them to reprioritize. Meanwhile, we are receiving sample data from Freightwaves and the methodology to ingest this data is understood.

Data services: We also spent significant amount of time in tracking down the data ingestion problems in RDS and fixed issues originating due to the change in data fields of RDS data source and multiplicity of duplicates. We also supported various tasks on the project and co-related projects (such as SMART Mobility Toyota project) in their data needs, including support on using the GridSmart API, CTwin's GridSmart service, and troubleshooting issues with data quality (such as incorrect zone definitions in GridSmart) and availability.

Next-generation data lake: Having learned about the nuances and challenges of data availability needs for a system such as CTwin, we have been working on a small-scale next generation data lake prototype using Amazon's S3 buckets.

Real-time alerts: In preparing for the experiment that is currently running 24/7 along the Shallowford Rd. corridor, an alerting system has been developed to email or send text message to subscribers to notify key personnel of slowed speeds along with gaps in pulling new signal timings.

Data Science:

Scaled up Signal performance assessment: New Jersey Institute of Technology (NJIT), our new partner in this work, under contract will be enhancing the codebase for calculation of Automated Traffic Signal Performance Metrics (ATSPMs) established in an earlier phase of the project. Data procurement continues to proceed forward. Data samples for real-time Wejo (not just archived) were received and validated. The team is moving forward for a large data licensing procurement that will serve the needs of the ATSPMs as well as a broader research data set for the Regional Mobility project.

For the Incident Detection, we developed a proof-of-concept algorithm that consumes data from a single sensor given data scarcity at the beginning of the quarter. We simulate the real-time capability of the algorithm by replaying historical data and demonstrate promising results. So far, this work has used historic RDS data and was validated against Hamilton County 911 data. We expanded the FFT-based algorithm for an approach that allows handling on-line data. We focus on TSA speed forecasting and use the error of the predicted value vs. actual speed to pinpoint anomalies

Video Detection for car and truck volume counts and relative speed calculation: While the early result on video detection for car and truck volume counts from one camera was promising, there are challenges as well as opportunity for expansion and improvement. We set up our system to stream videos from 10 cameras around the area near Shallowford Road. The volume counts are streamed into a different topic in Kafka, then store in Druid for analytics. Efforts are underway to scale up.

Modeling and Simulation:

Expand HPC and AI methods to prototype expanded simulation area: The Origin-Destination (OD) demand matrix used within the simulation tools are obtained from the larger Chattanooga travel demand model. However, this OD matrix only represents average weekday conditions and does not reflect the day-to-day variations in travel demand. As part of the task, near real-time hourly volumes are being generated by AI models and the OD matrix (from the travel demand model) is iteratively adjusted such that link volumes are consistent with the hourly volume estimates.

Modeling and Simulation Task: We expanded the use a machine learning based method to estimate the ground truth link-level volume estimates in the region of Chattanooga and Georgia. We used high-performance computing (HPC) to run regional simulation, each hour of the day, and create volume and speed outputs to be fed into a graph neural network model to estimate edge-level speed and volume. This is still ongoing work. We also used HPC to prototype OD demand calibration using Simultaneous Perturbation Stochastic Approximation (SPSA) from ground truth link-level volume estimates. Finally, we validated the expanded Chattanooga-Georgia network to enable simulations.

Cyber-Physical Control:

AI-based traffic signal control: We are implementing a framework that enables RL to be applied in dual-ring controller by constructing a differentiable convex optimization layer at the end of neural network to ensure that the output actions of RL comply to the constraints that defined by National Electrical Manufacturers Association (NEMA) standards. Till this point, there is no literature can use RL to optimize dual-ring controller timings. We overcame this barrier by adding a differentiable convex optimization lay to the neural network in the RL agent that will force the outcome into a feasible space for the signal control and still trainable.

24x7 Control experiment deploying a real-time traffic signal control algorithm: We successfully executed 3 weeks of 24x7 traffic signal control experiment in Chattanooga, TN. A previous real-time traffic signal control experiment was conducted in June and that work was included in a TRB annual meeting paper which was accepted for presentation in January 2022. This experiment scales up the previous June experiment both spatially and temporally. The data is being analyzed at the time of writing this report.

Control experiment planning for Downtown Chattanooga: For this area, we have modeled the dynamics of traffic delay and traffic volume by historical data using machine learning and system identification techniques. Preparations are ongoing for field experiment.

Conclusions

Overall, the project is progressing well with key artifacts being produced in all areas of scoped work. The situational awareness, data science, modeling and simulation, and control work is reaching a level of maturity and are expected to deliver the demonstrations of the concepts in the second year of the CTwin effort.

Key Publications

1. Invited talk at SOS24 Workshop, Swiss National Supercomputing Centre, St. Mortiz, Switzerland, 10–24 March 2021 (virtual).

2. Invited talk, Architecting the Future of your Smart City, Public Sector Network, Online, 17 March 2021 (virtual).

3. Invited talk, CTwin – Developing a Transportation/Mobility Digital Twin for Chattanooga, 24 February 2021, Jefferson Laboratory (virtual).

4. Invited talk, Mobility Digital Twin for Chattanooga, AI for Robust Engineering and Science, 19–21 January 2021 (virtual).

5. Invited talk at Internet of Things in Intelligent Transportation systems: Opportunities and Challenges, 20 October 2020 (virtual)

6. Invited talk at TennSMART Consortium meeting, 23 July 2020, (virtual).

7. Qichao Wang, Joseph Severino, Juliette Ugirumurera, Wesley Jones, Jibonananda Sanyal, "Offline Arterial Signal Timing Optimization based on Virtual Phase Link Model - A Real-world Case Study", *Transportation Review Board*.

8. Joseph Severino, Yi Hou, Ambarish Nag, Jacob Holden, Lei Zhu, Juliette Ugirurmurera, Stanley Young, Wesley Jones, Jibonananda Sanyal, "Real-Time Highly Resolved Spatial-Temporal Vehicle Energy Estimation Using Machine Learning and Vehicle Probe Data", *Transportation Review Board*.

9. Anne S Berres, Haowen Xu, Sarah A Tennille, Joseph Severino, Srinath Ravulaparthy, Jibonananda Sanyal, "Explorative Visualization for Traffic Safety using Adaptive Study Areas", *Transportation Research Record*, 15 January 2021.

10. Qichao Wang, Joseph Severino, Juliette Ugirumurera, Wesley Jones, Jibonananda Sanyal, "Offline Arterial Signal Timing Optimization for Closely Spaced Intersections", *2021 IEEE Green Technologies Conference*, 7 April 2021.

11. Haowen Xu, Anne Berres, Chieh Ross Wang, Tim J LaClair, Jibonananda Sanyal, "Visualizing Vehicle Acceleration and Braking Energy at Intersections along a Major Traffic Corridor", Proceedings of the *Twelfth ACM International Conference on Future Energy Systems*, 22 June 2021.

12. Joseph Severino, Ambarish Nag, Yi Hou, Juliette Ugirumurera, Jeff Cappellucci, Jacob Holden, Wesley Jones, Jibonananda Sanyal, "Development of automated pipeline for time-resolved link-wise vehicular energy consumption in the Chattanooga, TN road network", *CoDA 2020*, 25–27 February 2020, Santa Fe, New Mexico.

13. Anne Berres, Haowen Xu, Sarah Tennille, Srinath Ravulaparthy, Ambarish Nag, Jibonananda Sanyal, "Traffic Flow Performance Analysis through Visual Analytics", *DOE Computer Graphics Forum (DOECGF)*, 28–30 April 2020, Santa Fe, New Mexico.

14. Haowen Xu, Jibonananda Sanyal, Anne Berres, "Optimization of Network Datasets for Web-based System using Composite Bezier Curves", *American Association of Geographers Annual Meeting*,6-10 April 2020, Denver, Colorado.

15. Haowen Xu, Anne Berres, Jibonananda Sanyal, Srinath Ravulaparthy, "A Client-side Web Application for Visualizing Massive Regional Mobility Data Collected from Real-time Traffic Sensors", *American Geophysical Union Fall Meeting*, 2019, San Francisco, California.

Acknowledgements

The project team remains grateful to Prasad Gupte and Heather Croteau for their continued support and constructive feedback throughout the execution of the project.

I.2.3 Ubiquitous Traffic Volume Estimation through Machine Learning Procedures (NREL)

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Start Date: September 1, 2019 End Date: September 30, 2021
Project Funding: $975,000 DOE share: $500,000 Non-DOE share: $475,000

Project Introduction

High-quality traffic volume data is critical for transportation planning, operations, and travel-energy calculations. However, vehicle count data from roadside sensors is very sparse owing to high capital cost of installing, and on-going maintenance of electronic sensor equipment. This project aims to bring to market a first of its kind traffic volume data product that provides accurate estimates of traffic volumes across the entire road network for all times (24x7) and all locations (100% coverage). This product greatly improves the coverage and quality of traffic volume information by combining commercial probe traffic data with traditional traffic measurement using state-of-the-art machine learning techniques. Commercial probe traffic data has already revolutionized travel time and speed reporting both for government agencies as well as general travelers (through applications such as Waze and Google Maps). With increasing ratio of probe vehicles in the traffic stream, the number of observed probes can be combined with other data using machine learning (ML), to produce estimates of traffic volume with a high degree of statistical confidence. Combining the vehicle probe data with other data (speed, weather, and a sensor-based calibration network) using ML methods provides the opportunity to scale quality volume measures network-wide cost effectively. Conventional sensor-based vehicle counts, be it radar, pneumatic tubes, or inductive loops, represent the current state-of-the-art. Such devices provide volume data at sparse locations and are too expensive to scale. NREL's method provides a complete operational picture of traffic flow everywhere on the network and at all times and does so at a greatly reduced cost compared to adding additional sensors. The basic method has been demonstrated by NREL in collaboration with the I95 Corridor Coalition and the University of Maryland (UMD), under a grant from the Federal Highway Administration (FHWA). The results have prompted the FHWA to investigate applications for estimating average annualized daily traffic (AADT) to complement existing data collection. At full scale deployment, this technology can provide a measure of central tendency of traffic volume, as well as monitor the roadways in real-time for perturbations resulting from unusual events.

The commercial partner on this project TomTom, Inc., is one of the major suppliers of in-car location and navigation products and services. TomTom's products include portable navigation devices, in-dash infotainment systems, fleet management solutions, maps, and real-time services. The Traffic and Travel Information department at TomTom collects and evaluates anonymous location information from connected devices and connected cars enhanced by external sources. These data are on the one hand used for live traffic information and on the other hand stored in a database for further evaluation. The live traffic data allow precise measurement of travel times or current speeds on the road network and can be enhanced by additional information required for various in-car applications. The historic probe vehicle data allow broad and detailed analyses on precise time-dependent behavior of traffic flow over complex road structures. TomTom possesses a massive store of probe vehicle data (from hundreds of millions of probes), which is a key input to the volume prediction algorithm proposed in this project. Over the years, TomTom was kept informed of NREL's work on ML-based volume estimation methods. Encouraged by the performance of the algorithms, TomTom has partnered with NREL to bring the lab developed ubiquitous volume estimation methods to market.

Objectives

The primary objective of this project is to increase the observability of traffic volume information. With increasing proliferation of technology in the form of automated, connected, electrified, efficient, and shared vehicle systems, it is critical now more than ever to have an accurate understanding of how much traffic is on the roads for each hour of the day, and each day of the year everywhere on the network. Such information has enormous utility in transportation as well as energy domains. Transportation planners can use this information to check the adequacy of existing transportation infrastructure. Traffic operations personnel can make use of this information to effectively re-route the traffic in case of unexpected network congestion events. The end goals of the project are:

1. To develop machine learning based estimation models that can theoretically accurately predict traffic volumes anywhere, anytime, and for any functional road class (freeway, arterial, major/minor collector etc.). Acceptable error bounds (for the estimation models) have already been established based on feedback from various state DOTs. The project team will strive to develop models that meet the set error thresholds (accomplished in FY20).

2. To test the spatial transferability of the volume estimation models, and determine the feasibility (or the lack thereof) for utilizing a traffic volume model estimated in one state to estimate traffic volume in a different state (accomplished in FY20).

3. Extend the models developed in step one to generate additional model outputs such as Average Annual Daily Traffic, and energy consumed at the level of roadway segment (accomplished in FY21).

4. To develop anomaly detection methods that can identify erroneous input data and tag the data for review and/or deletion. Identifying bad data can help develop models that perform better (accomplished in FY21).

Approach

Average Annual Daily Traffic Estimation: Average Daily Traffic (ADT) is the volume of traffic moving in both directions on a highway for the most average traffic day in the year for 24 hours. ADTs are annualized by applying adjustment factors from nearby permanent count stations. The resulting measure, labeled average annual daily traffic (AADT) is often used in for transportation planning, and performance measurement. In this effort we explored estimating AADT using two methods

- ***Method 1***: Hourly volume estimation models are estimated based on ground truth data from Continuous Count Stations (CCS) in each state. The estimated model is applied to obtain hourly volumes at all CCS stations (for the holdout sample). The hourly volumes are first aggregated to obtain ADT, and the ADTs are averaged out to obtain AADT.

- ***Method 2****:* Direct ADT estimation models are estimated based on data from all CCS in the state. The estimated model is applied to obtain ADT at all CCS stations (for the holdout sample). The ADTs are averaged out to obtain AADT.

Directly estimating ADTs is more computationally efficient than the hourly estimation method (as we must estimate one 'daily' volume in place of 24 'hourly' volumes), but the computational efficiency comes at the cost of model accuracy. Roughly speaking, method 2 takes about a third of the time to apply compared to method 1.

Anomaly Detection Methods: The goal of this exercise is unsupervised detection of anomalous traffic patterns that are very likely to be the result of sensor error or transcription error (i.e., incorrect measurements of the real traffic volume at a point in time). Speed data and traffic volume data from orthogonal sources (TomTom based probe speeds, and HPMS traffic counts) is leveraged for this exercise. Based on the literature reviewed, we identified two anomaly detection methods namely

- ***Local Outlier Probability or LoOP method*** (based on Local Outlier Factor proposed in Breunig et al [1]). Using the LoOP method, each observation in TomTom data is assigned a probability of being an outlier. Independently, the LoOP method is applied on the continuous count station data to assign outlier probability values to observed traffic volumes. If an observation from both datasets for the same period (an hour or day) greatly varies in probability of being an outlier, then the observation is anomalous.

- ***Isolation Forest***. In isolation forest method, anomalies are identified based solely on the concept of isolation without utilizing any distance or density measure (e.g., k-nearest neighbors, LoOP) which is unique in comparison other existing methods (Liu et al., [2]). The isolation forest algorithm sets a score between zero and one for each observation (similar to LoOP) that rates its isolation relative to other observations in the data set across all variables of interest. This score is different than LoOP in that it should not be considered a probability of outlierness: values close to zero are not able to be well isolated, scores close to 0.5 indicate average ability to isolate, and scores close to 1.0 indicate high ability to isolate (and thus high outlierness).

While these approaches are unsupervised, there is value in identifying some observations as very likely to be anomalous by estimating the maximum capacity of lanes on roads and comparing to observed volumes. Federal Highway Administration's Simplified Highway Capacity Calculation Method (FHWA [3]) is used to tag anomalous observations before applying the isolation forest method.

Results

Average Annual Daily Traffic Estimation: Separate AADT estimation models are estimated for freeways and off-freeways in Massachusetts. Data for 47 CCS on Freeways, and 15 CCS on off-freeways, for the calendar year of 2019 is used for model estimation and validation.

Table I.2.3.1 AADT Estimation Results for Massachusetts

Roadway Type	Method	WAPE*	MAE**
Freeways	Hourly Traffic (Method 1)	16.2%	7,307
	Daily Traffic (Method 2)	16.3%	6,865
Off-freeways	Hourly Traffic (Method 1)	16.6%	1,379
	Daily Traffic (Method 2)	22.2%	1,697

$$^{*}\ \text{WAPE} = \frac{\sum_{i=1}^{N}\left|V_i - \widehat{V_i}\right|}{\sum_{i=1}^{N}|V_i|}$$

$$^{**}\ \text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|V_i - \widehat{V_i}\right|$$

V_i → observed volume; $\widehat{V_i}$ → estimated volume; N → number of observations

As observed from Table I.2.3.1, for freeways, the ADT-based AADT estimation results are as good as the hourly volume-based estimation results. So, going with the ADT based model would be preferred for the benefit of computational efficiency. For off-freeways, the ADT-based AADT estimation results are slightly inferior (about 5% lower accuracy) compared to the hourly volume-based estimation results. So, an hourly based model would be the preferred option if accuracy is important. The estimated models are applied to obtain AADTs on all roadway links in Worcester, MA (shown in Figure I.2.3.1).

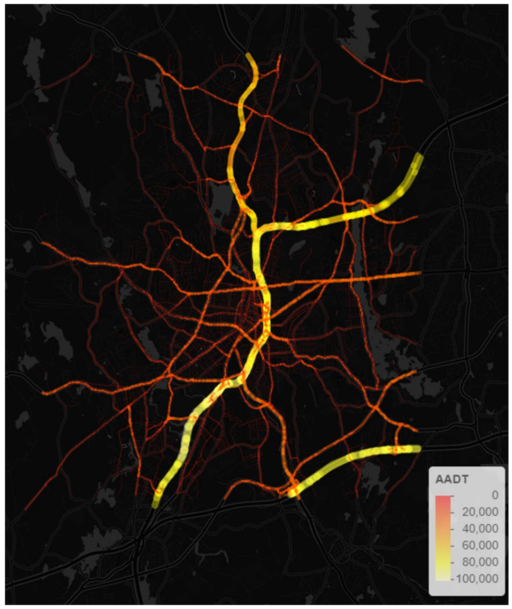

Figure I.2.3.1 AADT on all freeways and off-freeways in Worcester, MA

Anomaly Detection Methods: Using a LoOP threshold of 80%, there were 58 (0.98%) station-days across 15 different stations out of 27 in North Carolina detected as anomalous (12 stations had no detected anomalies), and 59 (0.62%) station-days across 11 different stations of 18 in Massachusetts (7 stations had no detected anomalies). In general LoOP detected anomalies pertaining to higher magnitude of volumes. Figure I.2.3.2 shows an example of the anomalies detected by LoOP. It is important to keep in mind that this is an unsupervised problem, and thus except for applying capacity estimates, we do not know if observations are truly anomalous or not, but with domain expertise, we can infer contextual likelihood of truly anomalous events that may not violate upper capacity limits.

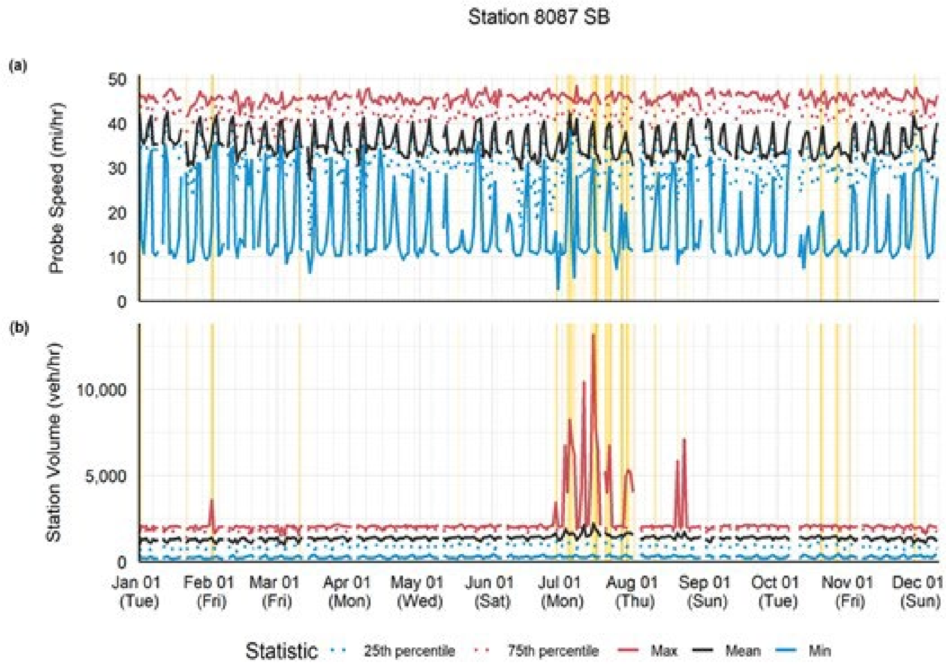

Figure I.2.3.2. Station example in MA of detected anomalous days that look close to expected. Yellow shading indicates higher probability of anomalies such that the more intense yellow is a higher LoOP score (higher probability).

The pre- and post- anomaly detection datasets for both regions were run through the volume estimation algorithm. Table I.2.3.2 shows the summarized results before and after anomaly detection in terms of weighted mean absolute percentage error (WAPE) and mean absolute error (MAE). The removal of potential anomalies is shown to have a very minor but positive impact on volume prediction models. In MA, off-freeway volume prediction performance (measured by WAPE) improved by 0.9% from 31.0% to 30.1% along with a decrease in MAE from 114 veh/hr to 110 veh/hr. In NC, off-freeway volume prediction had a consistent 37.4% MAPE before and after, but after anomaly removal, the MAE decreased from 68.2 veh/hr to 68.0 veh/hr (a 0.3% decrease). Overall, very minor impacts agree with the size of removed observations (<1%).

Table I.2.3.2. Anomaly Detection Results for Two Regions

	Pre-Anomaly Detection		Post-Anomaly Detection	
	WAPE	**MAE**	**WAPE**	**MAE**
MA off-freeway	31.0%	114 veh/hr	30.1%	110 veh/hr
NC off-freeway	37.4%	68.2 veh/hr	37.4%	68.0 veh/hr

Like LoOP, isolation forest still favors high volume days as being anomalous in both cases. In addition to data from single states (i.e., MA and NC), data from both states was pooled together to see if the anomaly detection method will benefit from seeing a wider variation in traffic volume data. Figure I.2.3.3 shows the maximum daily change in hour-to-hour volumes versus the isolation score. Increases to the maximum daily change in volume correlates to a higher isolation score. The two-region meta model shows improvement in separating the extreme known anomalies from other observations. Since the order of magnitude of anomalies observed by isolation forest is roughly the same as the LoOP method, we did not carry out an exercise to evaluate model performance before and after the anomalies are removed.

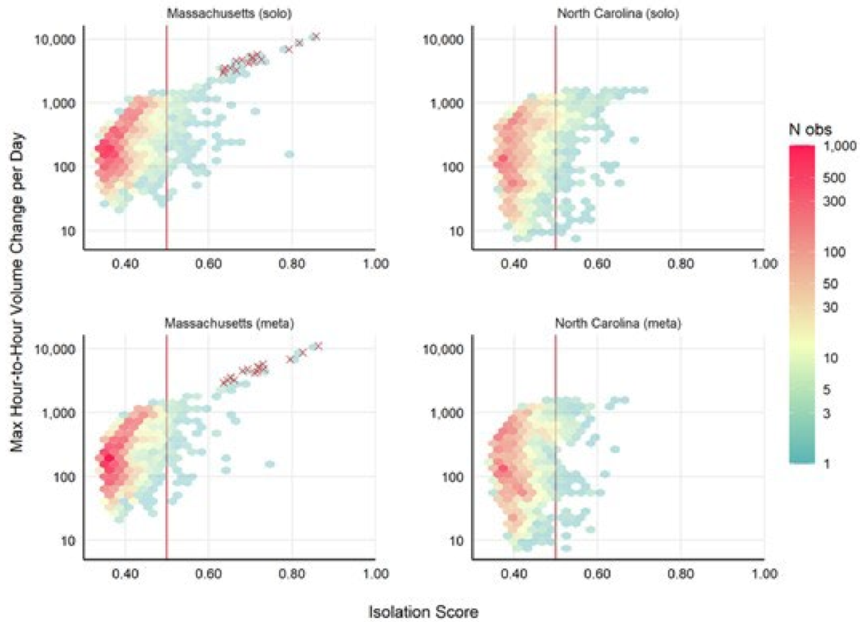

Figure I.2.3.3. Maximum hour-to-hour change in observed traffic volume versus the isolation score

Conclusions

- AADT Estimation analysis reveals that the tradeoff between computational efficiency and accuracy varies based on the type of the roadway. While the more computationally efficient method (daily aggregation) is ideal for freeways, off-freeway would benefit from the higher accuracy provided by the less computationally efficient method.
- While the chosen anomaly detection algorithms can detect some anomalies in the data, the approaches appear to skew towards extreme or high-volume days as low volume observations are common on off-freeway roadways. It was also noticed that the approaches tested are not robust to structural changes over time or temporal patterns with large swings in magnitude.
- A web dashboard was developed to visualize the outputs of volume and AADT estimation models. Currently in discussions with the industry partner to incorporate these into their product platform.

Key Publications

1. Hoehne, Chris, Venu Garikapati, Yi Hou, and Stan Young. Demonstrating the Improvement (or the Lack Thereof) in Volume Estimation Results After Implementing Anomaly Detection. (2021). In preparation for submission to a journal.

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2. Liu, Fei Tony, Kai Ming Ting, and Zhi-Hua Zhou. "Isolation-based anomaly detection." *ACM Transactions on Knowledge Discovery from Data (TKDD)* 6, no. 1 (2012): 1–39.
3. FHWA (Federal Highway Administration). Simplified Highway Capacity Calculation Method for the Highway Performance Monitoring System. In *Simplified Highway Capacity Calculation Method*. (2020). Retrieved from https://www.fhwa.dot.gov/policyinformation/pubs/pl18003/chap02.cfm.

Acknowledgements

- The PI would like to acknowledge the efforts of the NREL team (Yi Hou, Chris Hoehne, Rohit Kavikondala, and Stan Young) in the development of the AADT estimation models and testing anomaly detection methods.
- The project team offers thanks to Danielle Chou and Erin Boyd at DOE-HQ for their continued support and encouragement throughout the course of this project.

I.2.4 Applying Artificial Intelligence (AI) Based Signal Coordination and Controls for Optimized Mobility for the Nimitz Highway and Ala Moana Boulevard Arterial in Honolulu

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

Project Introduction

Advances in wireless-driven vehicular communications have greatly facilitated emerging cooperative intelligent transportation control system operations and enabled many smart traffic control and management applications to improve traffic safety performance and operation efficiency [1]. V2X communications allow vehicles to communicate with other vehicles (vehicle-to-vehicle, V2V); infrastructure (vehicle-to-infrastructure, V2I); pedestrians, bicyclists, and devices (vehicle-to-device); and internet through cellular signal networks and/or DSRC technologies. The information exchanges supported by V2X communication systems can effectively balance traffic demand distribution among traffic networks and facilitate traffic flow progression. With the new data platform, it is now possible to demonstrate AI-based modeling and control to optimally coordinate signal controls for the system.

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. This constitutes a dynamic and unknown stochastic system, and its modeling is generally difficult to perform using first-principles 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. 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 the feedback 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.

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. These shortcomings have limited the current research on AI for mobility at the simulation level. Moreover, energy efficiency has not been well addressed for these AI-based modeling and controls. 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.

The project brings together expertise of the US Department of Energy's (DOE's) Oak Ridge National Laboratory (ORNL) on artificial intelligence (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 1) for the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu, Hawaii. The goal is to achieve at least 15% energy savings and 25% reduction in travel delay. New Econolite control systems are being installed for full vehicle-to-everything (V2X)–enabled connectivity for improved traffic flow with a new system-level operational and data access platform located at UH (Figure 2). This information platform and the signal system is unique and the most advanced of its kind in the United States as the result of a $6 million project recently funded by the State of Hawaii Department of Transportation (DOT), providing unique, full access to the real-time data and user-friendly control system interface ideally suited for testing various advanced modeling and signal control algorithms. The proposed project aims to apply AI-based modeling and control using real-time data to construct an AI-based closed-loop coordinated signal control systems for 34 intersections as shown in Figure 1. The proposed research seeks solution to the following problems:

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

b) Developing optimal AI control for the traffic flow system with minimized energy usage for the 35 intersections in the arterial system shown in Figures 1 and 2, leading to the real-time AI-based closed-loop coordinated signal control in Figure I.2.4.1; and

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

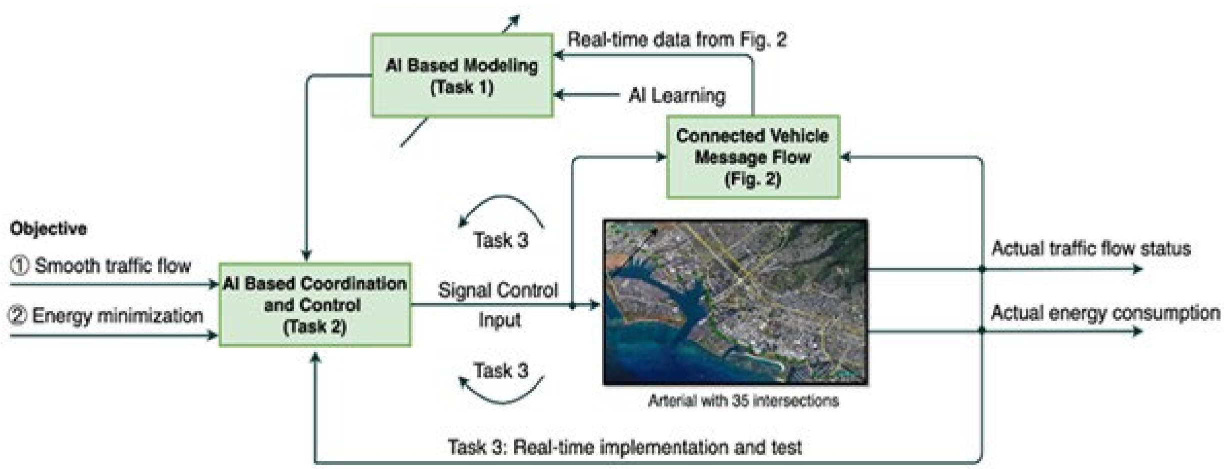


Figure I.2.4.1 The proposed real-world implementation using AI techniques

Figure I.2.4.2 shows this newly developed system and platform by UH and Econolite Systems for the arterial in Honolulu, where the available data are listed in the following table.

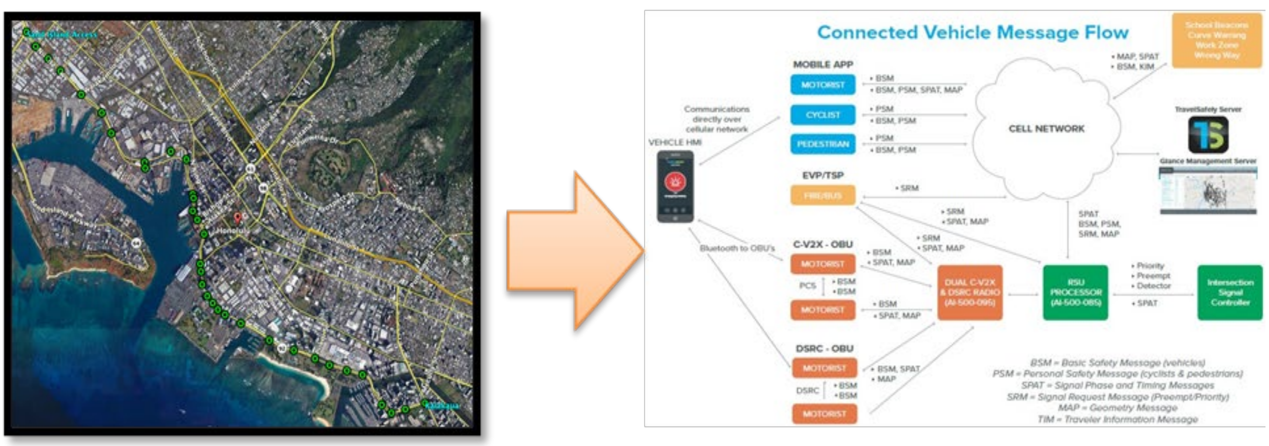


Figure I.2.4.2 The Econolite System Data Platform

Objectives

The goal of this project is to apply and evaluate an AI-based traffic control system enabled by cutting-edge V2X 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 (Figure I.2.4.1 and Figure I.2.4.2).

Approach

To achieve the project, the following tasks will be performed:

Task 1: AI-based modeling (5 months, ORNL and UH): The task is to use the real-time data (Data 1–4) in Table I.2.4.1 to build up MIMO AI-based data-driven models using an artificial neural network and neuro-fuzzy rules (developed by the PI). The model characterizes the dynamic and stochastic relationship between the inputs and the outputs and exhibits fast responses to dynamic variations of the system.

Task 2: AI-based control (7 months, ORNL/Econolite/UH): This task aims to develop AI-enabled signal coordination controls that can optimally manipulate the signal timing of the 34 intersections along the arterial in Figure I.2.4.1, where cascaded intelligent control will be used to obtain optimal signal timing for smooth traffic flow with energy savings. Using the data collected from the newly commissioned infrastructure and sensors from the arterial, producing a good estimate for the energy consumption along the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu is now possible. This estimate enables a multi-objective optimization that has two objective functions for the traffic flow smoothness and energy consumption. Bayesian stochastic optimization will be used to obtain the control parameters and AI feedback control laws, which can also minimize the impact of randomness to the traffic flow.

Task 3: Real-world implementation (12 months, ORNL/UH/Econolite): Using the signal control and traffic flow real-time platform located at UH and Econolite, the AI-based modeling and control algorithms obtained in tasks 1 and 2 will be implemented, tested, and validated in terms of AI impact on efficiency of mobility.

Results

AI-based modeling: The team spent the first five months as planned to develop neural network-based models. Figure I.2.4.3 shows the signalized arterials to be modeled from the Econolite Systems interface, where the input is the signal timing plan at each intersection and the output is the traffic delays of different phases (left turns, right turns and straight movements). The modeling objective is to build up dynamic models that reflect the dynamics of the system; the data used were collected from Econolite systems.

Taking $u(k)$ as the input and $y(k)$ as the output vector that is composed of the signal timing plan (i.e., green light time duration under fixed cycle length) and the traffic delays for each phase (i.e., through movements, left turns, and right turns) at an intersection respectively, the dynamics of the system can be modeled as follows

$$y(k+1) = f(\,y(k), u(k), \omega(k)) \qquad (1)$$

where $f(\dots)$ is the nonlinear vector function representing the system dynamics, $\omega(k)$ is the random noise term, and k is the sample number, which can be a multiplication of cycle duration in signal timing control. As the system is nonlinear and non-Gaussian, a novel hybrid neural network (HNN) modeling is developed as described here. In this context, a dynamic model was considered that reflected the relationship between the input and the output. Moreover, to improve the model, traffic volume was also considered as an extra input. Thus, the system had two input vectors (i.e., signal time plan and traffic volume) and one output vector, traffic delays. The system model was therefore assumed as follows:

$$y(k+1) = Ay(k) + Bu(k) + f(y(k), u(k-1), v(k)) \qquad (2)$$

where $y(k)$ and $u(k)$ denote average delay per vehicle and green time for multiple intersections at time index k. $f(\dots)$ is an unknown nonlinear vector function to be learnt and $\omega(k)$ is noise. $\{A, B\}\}$ are the weight matrices to be identified simultaneously with the estimate for the unknown nonlinear dynamics.

Let NN be used to approximate $f(\,y(k), u(k-1), v(k))$ by $\hat{f}(y(k), u(k-1), v(k), \pi)$, where $v(k)$ denotes traffic volume; π groups all NN weights and biases. Then the training of the NN as well as the two matrices was to obtain accurate and reliable models for the traffic flow system. The objective of training was to minimize the following performance function:

$$\text{Min } J = \frac{1}{2}\left(\hat{y}(k+1) - y(k+1)\right)^2 \qquad (3).$$

To model the system in (2), relevant data from the seven intersections were collected along the arterial as shown in Figure I.2.4.3. For an example of the seven intersections, the details of the data collected are as summarized in the Table I.2.4.1.

Table I.2.4.1 Data Collection for HNN Modeling

Study area	Intersection 1–7
Date collected	March 3–5, 8–12, 15–19, 22-26, 29–31, April 1–2 (23 weekdays) in 2021
Time duration	4 pm – 7 pm
Signal timing	All phases of major and minor streets
Traffic volume	All movements
Traffic delay	All movements
Sampling index	Every five signal cycles (each cycle ≈180 s)

The modeling results were evaluated by mean absolute percentage error (MAPE), and the following figure shows the modeling error bars for all the 34 intersections. It can be concluded that the average errors are less than 10%—achieve our modeling milestone.

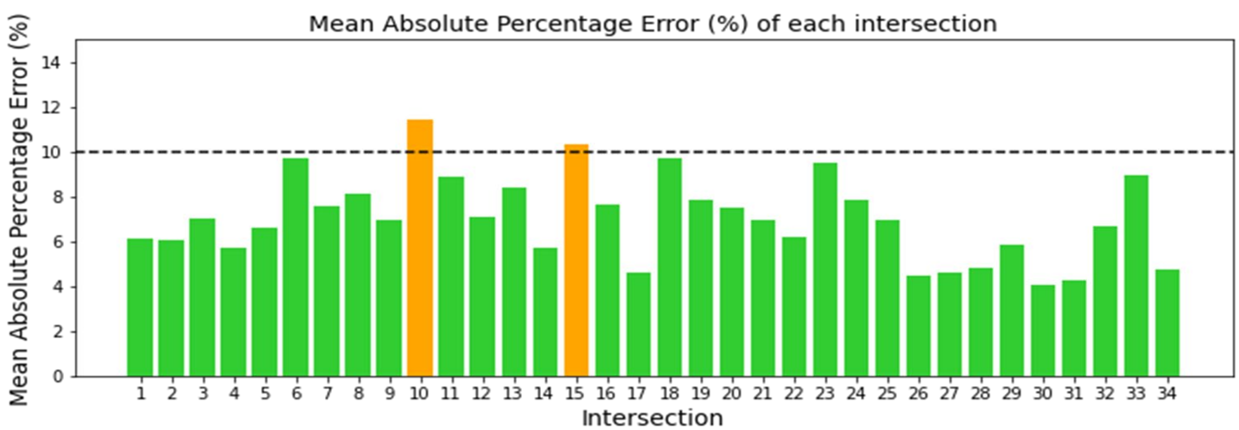


Figure I.2.4.3 The modeling error showing an average of less than 10%, with over 98% confidence interval.

In line with the above modeling error performance, the following figure shows a typical model testing result for a signal phase for the first intersection along the corridor.

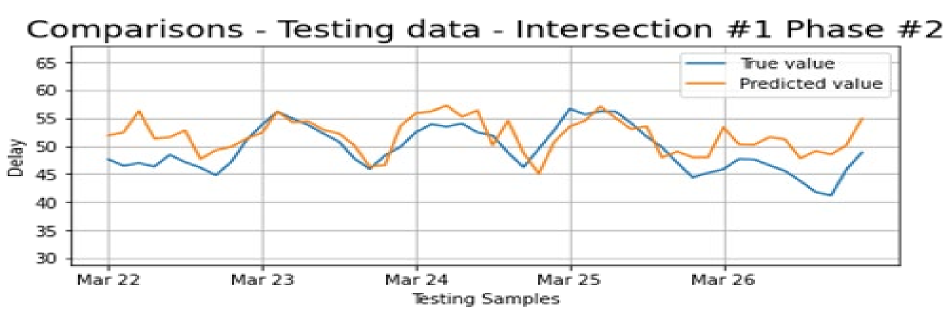
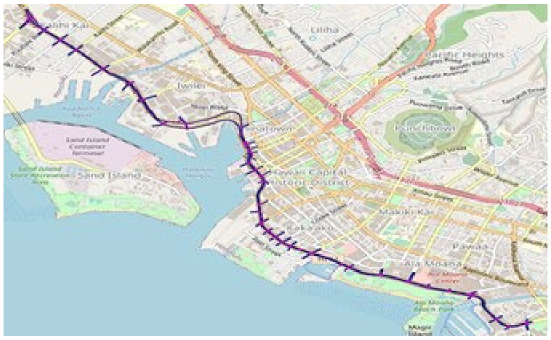
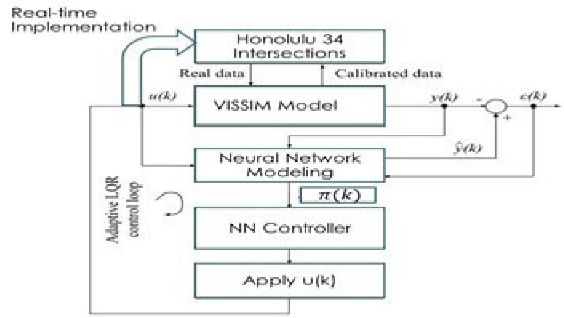


Figure I.2.4.4 A typical model testing result for a signal phase for the first intersection.

VISSIM system establishment for control system design: To establish the proposed AI-based control using the adaptive online models as shown in Figure I.2.4.1, a VISSIM simulation platform is being built where the idea is to use VISSIM system to test the modeling and control strategies for the corridor. Once the VISSIM simulation calibrated it will be used as an initial testing system to test the modeling and control algorithms. Once the VISSIM testing and validation are completed, the modeling and control algorithms will be applied to the actual signal control systems for the 24/7 real-time implementation as planned for FY22/23. Such a VISSIM simulation-based testing structure is shown in the Figure I.2.4.5.



(a)



(b)

Figure I.2.4.5 (a) The actual corridor in Honolulu (b) VISSIM simulation testing system

Conclusions

In FY21, the team has been focused mainly on the new modeling development for the 34 intersections, where data has been collected from the Econolite Systems platform and desired modeling results have been obtained showing an average modeling error of less than 10% with over 98% of confidence interval. This indicates that the new HNN modeling can be readily used for the AI-based control system design as shown in Figure 1. The team is also in the process to establish a VISSIM simulation testing system to accommodate the control algorithm design. A technical paper has been published at the 2021 Vehicular Conference in France as a keynote paper, which has received the **best paper award** from the conference as well.

Key Publications

1. H Wang, et al, Hybrid neural network modelling for multiple intersections along signalized arterials – current situation and some new results, *The 10th International Conference on Advances in Vehicular Systems, Technologies, and Applications*, VEHICULAR 2021, July 2021 – Nice, France (Keynote Speech).

2. H Wang, et al, Hybrid neural network learning for multiple intersections along signalized arterials: a microscopic simulation vs. real system effect, *International Journal on Advances in Networks and Services*, v 14 n 1&2 2021.

References

1. H Wang, M Zhu, W Hong, G Tao and Y Wang, Optimizing Signal Timing Control for Large Urban Traffic Networks Using an Adaptive Linear Quadratic Regulator Control Strategy, IEEE Transactions on Intelligent Transportation Systems, 2020 (Accepted and online)

Acknowledgements

The work performed is funded by the Vehicle Technologies Office of the US Department of Energy under the AI for Mobility program. This is gratefully acknowledged. The project team consists of researchers from ORNL (Chieh Wang, Yunli Shao, David Smith, Ti, Laclair, Jinghui Yuan), University of Hawaii (Guohui Zhang and Arun Bala Subramaniyan) and Econolite Systems (Jon Ringler and Nick Ullman). Their effort has made the project well on the track as planned. The team would also like to thank Danielle Chou, the program manager, for her great support of the project.

I.2.5 HPC-Enabled Artificial Intelligence for Connected and Automated Vehicle Development (ORNL, NREL)

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Start Date: October 1, 2020 End Date: September 30, 2021
Project Funding: $1,400,000 DOE share: $1,400,000 Non-DOE share: $0

Project Introduction

The goal of the HPC-CAVs project is to explore and develop the application of advanced AI and high-performance computing (HPC) throughout the connected and autonomous vehicles (CAVs) pipeline. The present state-of-the-art in AVs utilize AI primarily in visual image processing, and classical algorithms elsewhere. We are investigating the entire pipeline. Also, as DOE-sponsored research, our mandate is to understand the implications for energy usage and broader sustainability, not just the safe operation of a vehicle. We have developed a series of tools (described briefly below) that explore various avenues, mostly in the single-vehicle context. Going forward, our mission now is to scale these tools up, link them, and apply them to DOE-relevant cases.

Objectives

This project seeks to achieve the following objectives: 1) increase affordability, convenience, safety, and energy productivity of mobility, 2) reduce transportation fuel use/GHG emissions, 3) validate safety of automated vehicles through accelerated simulation environments, and 4) explore and validate innovative vehicle control strategies at the system level.

To demonstrate the achievement of these objectives, this project will:

- Demonstrate HPC-based ability to analyze large data sets from prototype self-driving vehicles and discover higher performance and resilient operating algorithms in an expedited cadence.
- Develop and demonstrate new machine learning based algorithms for vehicle operating controls that are capable of scaling to “Level 5” autonomous vehicle capabilities.
- Develop a virtual test environment capable of safely evaluating autonomous vehicle operating controls over millions of miles and scenarios/environments expected to be encountered. There is expected applicability to advanced conventional vehicles by examining electronic controls for powertrain functions.

Questions to be addressed:

1. How do we leverage machine learning for perception and control of a single autonomous vehicle given the constraints / objectives of safety, destination arrival, and energy efficiency? (FY19)

2. How do we leverage machine learning for perception and control of multiple autonomous vehicles given the constraints / objectives of safety, destination arrival, and energy efficiency? (FY20)

3. How do we leverage machine learning for perception and control of multiple autonomous vehicles in a connected environment given the constraints / objectives of safety, destination arrival, and energy efficiency? (FY21)

Approach

For FY21, ORNL and NREL explored a wide range of machine learning challenges for autonomous vehicles and developed key capabilities that address these challenges.

ORNL's research focused primarily on imitation learning, which emphasizes training neural networks from static data sets that cover a range of operating scenarios. In our efforts to apply our Multi-node Evolutionary Neural Networks for Deep Learning (MENNDL) software to the challenge of designing a perception neural network, we identified several gaps in the AI technology for autonomous vehicle perception neural networks: 1) real data sets do not cover all possible lighting conditions, 2) measurements of neural networks performance such as accuracy or loss functions did not adequately train the neural networks, and 3) there are no automated methods for performing test and evaluation of perception neural networks. In FY21, ORNL focused on developing the techniques, data, and algorithms needed to fill these gaps. We addressed these gaps by 1) developing a data generation code that works with the CARLA driving simulator to develop synthetic imagery to supplement real data, 2) developed an evaluation metric to assess how well a perception neural network perceives the environment effectively while driving, and 3) developed a new AI based system called Gremlin that automates the test and evaluation of perception neural networks and is capable of leveraging cloud computing or high-performance computing systems.

NREL's research focused primarily on reinforcement learning (RL), which emphasizes training neural network-based control policies using simulations that mimic the actual operating environments. There are many complex systems and subsystems involved in control of vehicles. Many steps involve uncertain models and optimizations that are intractable to do in real time. RL presents an alternative approach, requiring no models and no real-time optimization, and offering inherent robustness to stochasticity and uncertainty. It is therefore worthy of consideration as a way around some of the difficulties classical approaches face. In FY21, NREL pursued a range of activities: 1) computational scalability of RL; 2) trajectory following 3) cooperative driving and parking; 4) exploiting the modular pipeline for neural network "fusing".

Results

From ORNL, some of the key achievements were:

- Developed an initial prototype of MENNDL using CARLA to evaluate the driving behavior of neural architectures generated by MENNDL. This development supports the scalability of imitation learning. Furthermore, this development supports the transition away from evaluating perception networks for pixel level accuracy and toward driving behavior improvements.

- Development of a new artificial intelligence (AI) system called Gremlin for the test and evaluation of perception neural networks within a simulated environment. This fills a critical gap in the AI technology for autonomous vehicles.

- Scaled Gremlin to more than 500 nodes of ORNL's Summit supercomputer. Within 1 hour using Summit, Gremlin evaluated 748,325 equivalent miles driven under a variety of lighting conditions.

This enables significantly more scenarios per hour to be generated and perception neural networks to be evaluated.

- We have completed the Quantitative Evaluation Metric for use with both Gremlin and MENNDL. This metric measures the driving behavior as affected by a perception network. Inherently, the metric penalizes behavior that wastes energy by driving longer distances between 2 points (e.g., weaving, taking wide turns). This fills a critical cap in the AI technology for autonomous vehicles.
- Development of enhanced data generation code that creates synthetic imagery and ground truth needed for training perception neural networks. This code enables the generation of imagery data with variables to control the amount of pedestrian and vehicular traffic as well as weather conditions, sun position, and road maps. This fills a critical cap in the AI technology for autonomous vehicles.
- Development of a new synthetic data set for training perception neural networks that works in conjunction with real world data sets. This fills a critical cap in the AI technology for autonomous vehicles.

ORNL's research on perception neural networks has been presented to DOE's Office of Technology Transitions, General Motors (USA), Ford (USA), Volvo (Sweden), and Volkswagen (USA).

ORNL licensed MENNDL to General Motors in October 2020.

ORNL has open-sourced Gremlin (https://github.com/markcoletti/gremlin) and the data generation software as well as the synthetic dataset and will disseminate to partners and points of contact.

From NREL, some of the key achievements were:

- RL shows great promise in many control tasks relevant to CAVs, from low level actuation to smoothing of macro scale traffic. We have undertaken reinforcement learning (RL) projects in the following areas, and submitted 3 papers in Q4FY21:
    - Low level vehicle actuation for trajectory following. This study showed that RL, especially when combined with model predictive control (MPC), is competitive if not superior to state-of-the-art approaches.
    - High level control of multiple vehicles cooperatively smoothing/increasing traffic flow. This study demonstrated in the SUMO traffic simulator that vehicles can be trained to drive in a way that significantly increases average speed in a highway "weave" (on-ramp followed by off-ramp) scenario.
    - High level control of multiple vehicles cooperatively parking at a curbside. This study showed that RL significantly outperforms a plausible baseline approach to curbside parking. Here we also developed a custom simulator to target the exact characteristics of the problem we needed to capture, illustrating Einstein's famous principle that "everything should be made as simple as possible, but no simpler".
    - Infrastructure level control of cooperative driving to smooth traffic/increase flow. This study shifted our focus from control of vehicles to control of infrastructure, an attractive prospect in an era of mixed autonomous/traditional vehicles. The control "action" that the RL agent learned in this case was a road-segment by road-segment target speed. The segment speeds can then be broadcast to connected vehicles, an advanced version of dynamic highway speed limit signs currently in use (e.g., in places with variable winter driving conditions).

- Modular coupling of path planning and path following (to be completed FY22Q1 with carryover funds). This study (currently ongoing) is exploring the possibility of connecting two separately trained neural networks, one for path planning and one for path following, into a single combined network; first whether it is possible, and further, whether additional training of the fused network results in improved and/or otherwise interesting behavior (e.g., the output of the path planning network consists of waypoints for the path follower; but do the semantics change when the previous output layer becomes a "latent" space in the larger network?).

- We have studied in detail the high-performance computing scalability of RL in both CARLA-based and "gridworld"-based environments. Due to recently discovered principals regarding maximum "useful" batch size in deep learning, it is non-trivial if not (depending on the task) impossible to scale RL to large compute resources. This study uncovered the tip of a much larger iceberg surrounding fundamental scalability of RL and machine learning in general. The main takeaway is that there is a relationship between problem "difficulty" (a hard to quantify concept involving in RL the size of the state, observation, and action spaces and the complexity of the underlying simulation used for training) and maximum efficient batch size, and that the batch size limit is, generally, smaller than one would intuitively think. So, in some sense, we pay a price in *decreased* computational scalability for making our formulation as simple as possible.

Conclusions

In summary, our suspicion that there are many more aspects of the CAVs control pipeline amenable to AI (beyond perception), and suited to RL, has been repeatedly verified. Further work would bifurcate into:

- migrating our idealized simulation-based studies toward more realistic and eventually real-world application (e.g., trusting/constraining RL).
- discovering algorithmic enhancements to improve both performance and scalability, especially
  - hybridization of classical and AI approaches to take advantage of the best of each.
  - scaling of RL via innovative architectures (e.g., hierarchical approaches, local SGD).

NREL has open sourced the KRoad (https://github.com/NREL/K_Road) and KFlow software and will disseminate to partners and points of contact.

Key Publications

1. Shang Gao, Spencer Paulissen, Mark A. Coletti, and Robert Patton, "Quantitative Evaluation of Autonomous Driving in CARLA", From Benchmarking Behavior Prediction to Socially Compatible Behavior Generation in Autonomous Driving Workshop held in conjunction with the 32nd IEEE Intelligent Vehicles Symposium (IV), July 2021.

2. Mark A. Coletti, Shang Gao, Spencer Paulissen, Nicholas Q. Haas, and Robert Patton, "Diagnosing autonomous vehicle driving criteria with an adversarial evolutionary algorithm," in Proceedings of the 2021 Genetic and Evolutionary Computation Conference Companion, GECCO '21, (New York, NY, USA), (to be published), Association for Computing Machinery, July 2021.

3. Robert Patton, Shang Gao, Spencer Paulissen, Nicholas Haas, Brian Jewell, Xiangyu Zhang, Peter Graf, "Heterogeneous Machine Learning on High-Performance Computing for End-to-End Driving of Autonomous Vehicles", 2020 Society of Automotive Engineers World Congress Experience, April 2020.

4. Yi Hou, Xiangyu Zhang, Peter Graf, Charles Tripp, and David Biagioni, "A Cyber-Physical System for Freeway Ramp Meter Signal Control Using Deep Reinforcement Learning in a Connected

Environment", in 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), pp. 3813–3820. IEEE, 202

5. Hilary Egan, Yi Hou, Monte Lunacek, Qichao Wang, Peter Graf, "Reinforcement Learning for Autonomous Curbside Operations" submitted to IEEE Transactions on Intelligent Transportation Systems, 2021.

6. Yi Hou, Peter Graf, "Decentralized Cooperative Lane Changing at Freeway Weaving Areas Using Multi-Agent Deep Reinforcement Learning", submitted to IEEE Transactions on Intelligent Transportation Systems, 2021.

7. Charles Tripp, Sarah Aguasvivas, Xiangyu Zhang, Monte Lunacek, Peter Graf, "Autonomous Vehicle Trajectory Tracking via Model-Free Deep Reinforcement Learning", submitted to IEEE Transactions on Intelligent Transportation Systems, 2021.

Acknowledgements

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I.3 Core Simulation and Evaluation Capabilities

I.3.1 Livewire Data Sharing Platform (NREL, PNNL, INL)

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Start Date: October 1, 2018 End Date: September 30, 2021
Project Funding: $1,500,000 DOE share: $1,500,000 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 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's objective is to enable research, collaboration and data sharing by providing state-of-the-art data management capabilities and services. FY21 goals included the addition of targeted data, data quality characterization, and backend and user-facing features for a better user experience.

Approach

The Livewire Data Working group (DWG) was established to help identify data and feature priorities. This group includes members from five national labs and met multiple times. The Livewire team was able to use DWG feedback to drive implementation and planning of new features.

Now in its third year, Livewire augmented its catalog with additions from foundational projects Fleet DNA and the Transportation Secure Data Center and multiple other VTO- and non-VTO funded projects.

Results

Features added in FY21 increase usefulness of the platform to users and lay the foundation for future work.

Major features added to Livewire in FY21 include access management and the implementation of role-based member management. Requested by many users, these features are flexible and meet data owner needs by allowing project leads to manage who can access the data they share on Livewire.

The addition of a “click-to-request” workflow allows logged-in users to request access to restricted data from the dataset pages. Project leads manage permissions directly from the platform and can approve, deny, or follow up via email (see Figure I.3.1.1).

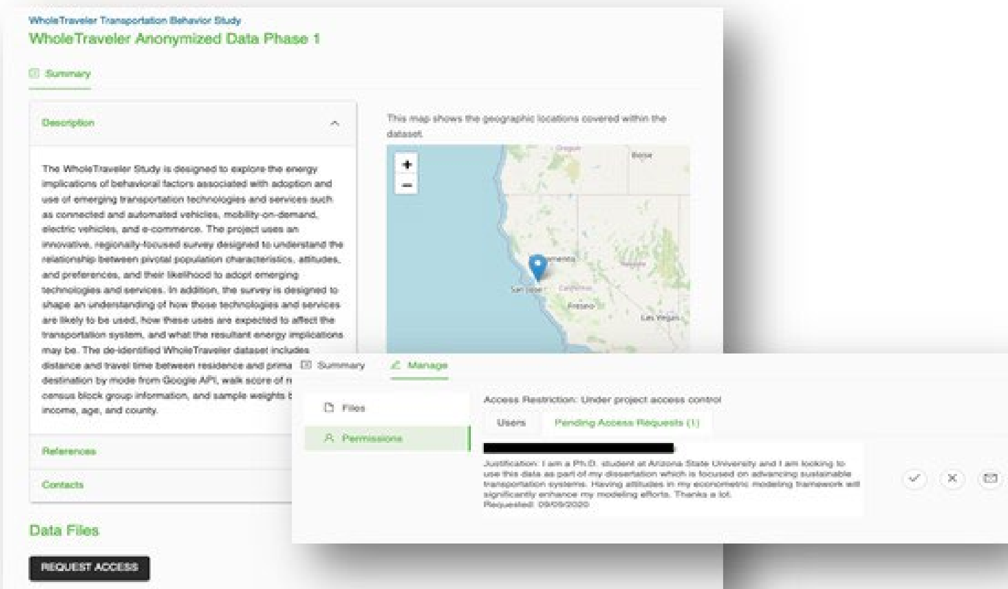

Figure I.3.1.1 Project leads can assign roles and manage access

Another key aspect to role-based member management is the ability for project leads to assign roles to members of their project team. Project leads manage access to data, editors can upload data, and project members have permission to view and access data.

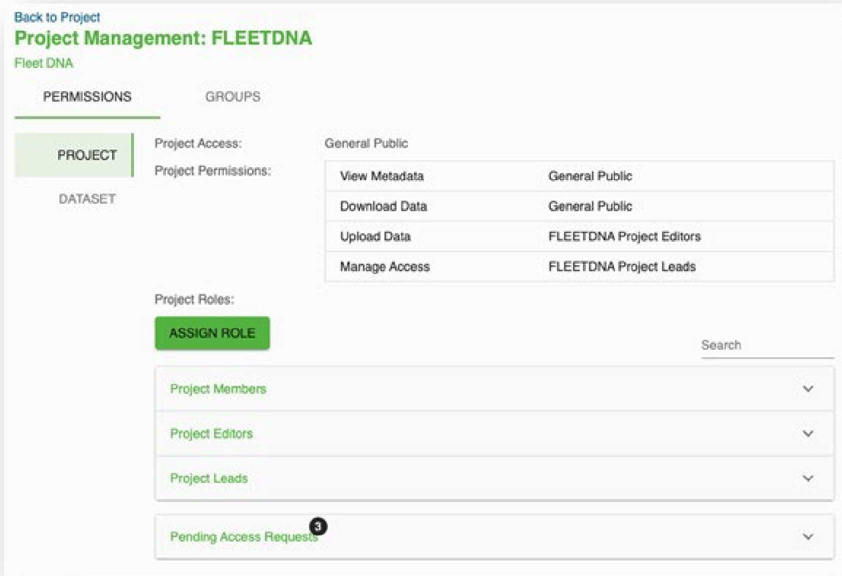

Figure I.3.1.2 Project leads can assign roles and manage access

Project and dataset pages were also redesigned to include detailed metrics about how many users view and access data. These metrics include number of views, number of downloads, number of files downloaded, and size of downloads.

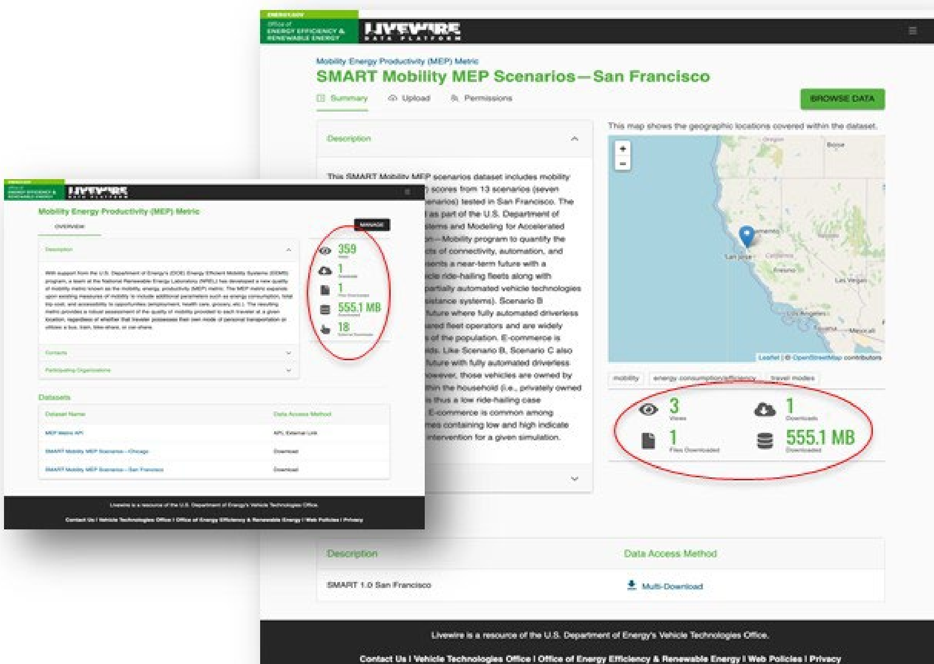

Figure I.3.1.3 Redesigned project and dataset pages include metrics

In addition to these usage and engagement metrics, the user interface (UI) was updated to support the addition of a quality metric. This metric is the product of an independent assessment performed by the Livewire team. It is focused on accuracy and completeness, where accuracy evaluates correctness of the data within a dataset using processes that identify instances of likely incorrect data such as:

- Statistical analysis and comparison of data values to expected distributions
- Domain- and units-of-measure-based reasonability checks
- Rates of occurrence in categorical data.

This assessment is complete for select datasets. Quality indicators supported by the UI include an overall score on the dataset page, an expandable panel with more detailed dataset metrics, and a dictionary that includes dataset and table-level quality metrics.

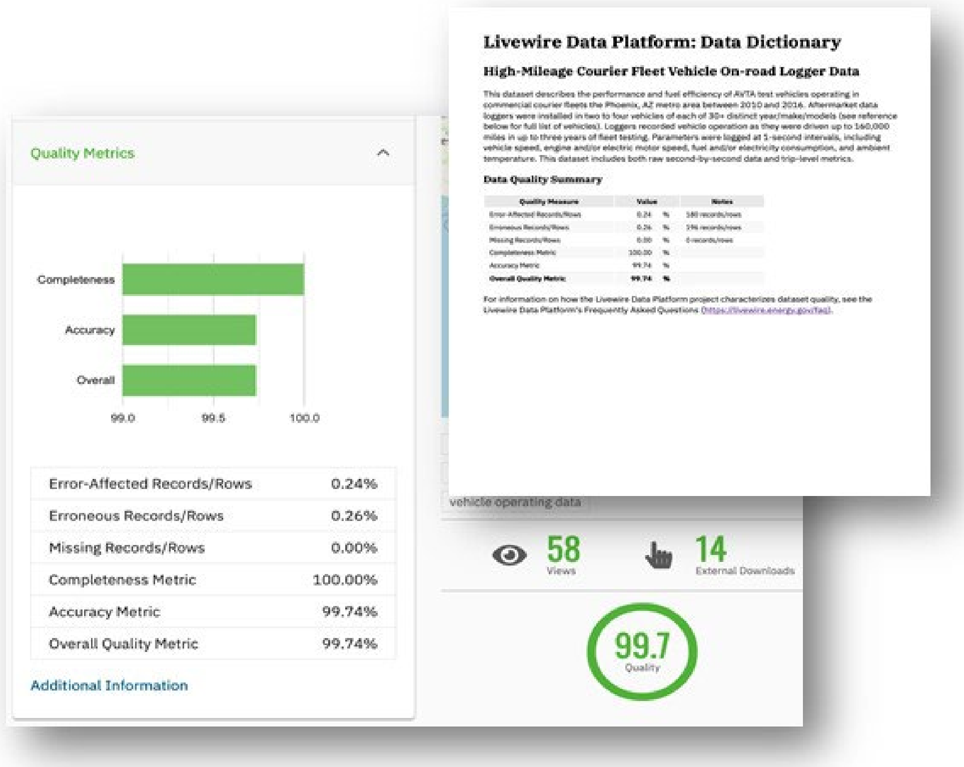

Figure I.3.1.4 Quality metric indicators are included on select dataset pages

Finally, significant progress has been made on the automation of tools to create detailed metadata. This detailed metadata is provided at the dataset level and contains information about a dataset, including characterization of data quality. Detailed metadata was added to six datasets.

Conclusions

The Livewire Data Platform 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 remove barriers to researchers finding and sharing the data they need and produce in answering important transportation questions. By handling storage and management, empowering project leads to manage access to their data, and driving catalog growth, Livewire allow 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 Danielle Chou, David Anderson, and Erin Boyd for their support.

I.3.2 RoadRunner – A Simulation Tool for Energy-Efficient Connected and Automated Vehicle Control Development (ANL)

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Start Date: October 1, 2019 End Date: September 30, 2022
Project Funding (FY20-22): $1,200,000 DOE share: $600,000 Non-DOE share (in-kind): $600,000

Project Introduction

Automotive engineers traditionally use drive cycles (vehicle speed as a function of time) to represent the actions of human drivers when simulating and testing vehicle powertrains in the design phase. However, this approach is not suitable for connected and automated vehicles (CAVs): speed is a control variable that is adjusted based on the surrounding environment the vehicle senses or communicates with. Since we found no tool dedicated to energy efficiency research in the context of advanced powertrain, connectivity, and automation technologies, we at Argonne have initiated the development of a new tool: RoadRunner. RoadRunner was instrumental in our research on energy-focused CAV control as part of the SMART 1.0 program and continues to support research in SMART 2.0. RoadRunner is a framework for simulating multiple vehicles with full powertrain models and their interactions with their environment. RoadRunner uses powertrain models from Autonomie, Argonne's established vehicle energy-consumption simulator, but adds new capabilities, such as multi-vehicle simulation, models of road characteristics, causal models of human driving, V2X ("vehicle to everything") communications, and sensors.

The goal of this project is to improve the technical quality of RoadRunner simulations and the user experience so that it meets the needs of automotive R&D engineers; and to create a first release of RoadRunner at the end of the project.

Objectives

The objective of the project is to bring RoadRunner closer to commercialization, with a robust first release that can be demonstrated outside the development team. This will be achieved through several outcomes described below.

RoadRunner release. We will develop a release of RoadRunner with the features of professional software:

- An easy-to-install package.
- A graphical user interface (GUI) with a good set of features, documentation, and training materials.

The release will also come with default models and scenarios for users to run out of the box. RoadRunner will include models of human drivers as well as CAV technologies, such as adaptive cruise control (ACC), cooperative ACC (CACC), V2X communications, intersection eco-approach, and so on.

A validated high-fidelity dynamic driver model. Our CRADA partner, Hyundai, identified human driver modeling as an essential feature of RoadRunner, as it provides a realistic baseline for research and development related to advanced driver assistance systems (ADAS) and CAVs. We will draw from the data provided by Hyundai to develop a new human driver to meet the needs and identify the most appropriate models and will calibrate the models using the data.

Real-world driving datasets for model development and validation. Our CRADA partner, Hyundai, will collect and share two datasets with Argonne that help characterize human driving.

1. A sample of recorded driving data from U.S. customers.
2. Data from a specially instrumented vehicle to be driven around southeastern Michigan over several months.

These two datasets are complementary: the customer data presents a broad array of real-world situations for a variety of drivers, geographical locations, vehicles, and powertrain types, while the data from the instrumented vehicle's camera and geographical coordinates will provide context from the surrounding environment. We will also develop a framework for processing the data, including automated data processing, quality checks, driving regime identification, traffic signal state extraction from video feeds, and addition of road attributes (e.g., speed limits, signs, etc.) via map-matching, etc.

Approach

RoadRunner release development

We will leverage existing tools and processes to accelerate the development and deployment of RoadRunner. On the GUI side, we will create a new RoadRunner workflow within AMBER, thus reusing many existing modules. We will also integrate RoadRunner into the same software deployment life cycle as AMBER and Autonomie, so that RoadRunner package generation is fast and robust for us developers, and user-friendly for our audience. We will then populate the release version with default models of CAV and scenarios, integrating with Autonomie's default vehicles, and ensuring proper functionality through automated testing.

High-fidelity dynamic human driver modeling

A good human driver model is critical in developing and evaluating CAV and ADAS technologies as it serves as the baseline. We developed a new high-fidelity dynamic human driver model that consists of a Perception and Decision (P&D) model to capture the cognitive process occurring in the human brain and an action model to capture human driving behaviors affecting the state of the vehicle based on Newtonian laws of motion.

- P&D model: determine the driving regimes (e.g., accelerating to increase speed, braking to stop) and its timing and duration based on current situation.
- Action model: generate optimal drivability trajectory of each driving regime using analytical optimal solutions minimizing jerk (the derivative of acceleration) energy.

Real-world driving data collection/exchange with Hyundai

In FY21, we formulated the sampling and grouping of customer data, based on population description tables provided by Hyundai, presenting precise specifications regarding vehicles, locations, and time frames. Hyundai's data team then shared this data with Argonne, where it can enter our data processing and analytics framework. Hyundai will also collect on-road driving data with instrumented vehicles, with Argonne's input on testing scenario design. The on-road testing data provides richer information with higher accuracy about the surrounding environment (e.g., video records) that is not included in the customer driving data.

Data analytics framework

As we will receive a very large amount of driving data from Hyundai, a data analytics framework is needed to improve data quality, increase data richness (e.g., identify driving regimes), and accelerate data analysis. The data analytics framework involves three main steps:

1. Data pre-processing: remove the undesired trip data (e.g., missing signals, short trip) and handle unrealistic behaviors from trajectory data.
2. Information extraction: extract the new useful information and convert it to time series data.
3. Data post-processing: "slice and dice" the pre-processed data through a multi-level process; it involves trip type identification, situation segmentation, driving regime isolation, and parameter extraction to yield richer information with labels.

Results

An easy-to-install RoadRunner release

RoadRunner has been released as a workflow in the AMBER Beta version, which can be used as a stand-alone tool or in conjunction with Autonomie. The documentation includes a training material providing step-by-step instructions with concrete examples and is available directly through a graphical user interface (GUI). A RoadRunner simulation study can be done through the following four steps using the GUI, as shown in Figure I.3.2.1.

1. Select vehicle: define vehicle string (e.g., vehicle model, initial distance gap with preceding vehicle).
2. Select route: define route by selecting the one from the library (and modifying it) or creating the new one using a road builder GUI developed in SMART 2.0 project.
3. Launch RoadRunner: run RoadRunner simulation for the pre-defined scenario.
4. Data analysis: plot the desired signals and analyze the results.

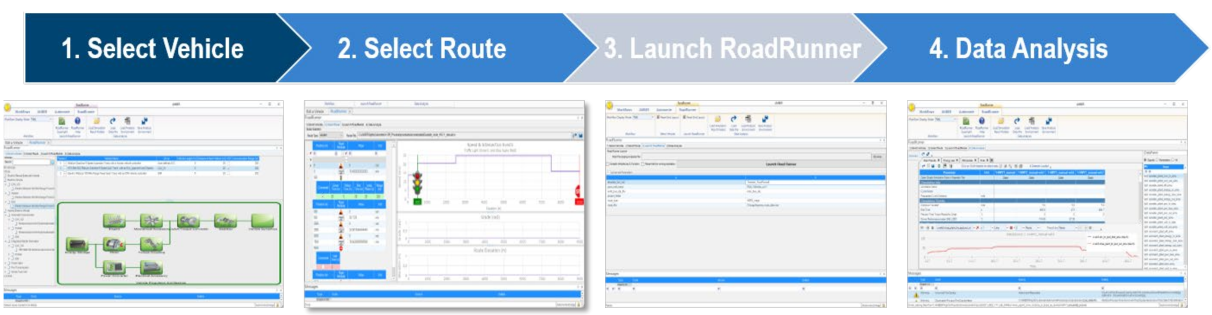

Figure I.3.2.1 RoadRunner workflow

The RoadRunner library in the AMBER Beta version includes 21 vehicle models, which are generated by a combination of 7 powertrain models (1 conventional, 1 EREV, 1 BEV, and 4 HEVs) and 3 following basic vehicle controller models (2 human driver models and 1 CAV controller model):

- Human driver model: analytical drivability-optimal model with a simple perception and decision model calibrated by a few data samples.

- IDM (intelligent driver model): the IDM combines the acceleration strategy that enables the vehicle to reach a desired speed with a braking strategy that prevents collisions while following the preceding vehicle with a constant desired time headway.
- Baseline CAV controller: the CAV controller model is based on the human model, but an eco-approach mode is added as it can use the signal phase and timing (SPaT) information from the next traffic light within the communication range.

We have also integrated RoadRunner into the AMBER software development lifecycle, as shown in Figure I.3.2.2. With the professional software lifecycle, we can facilitate maintenance and development for developers and ensure high-quality software for end users. First, JIRA server was set up to report bugs, feature requests, and track their progress. Seconds, we have set source code control, splitting core code and models for easier tool maintenance across multiple projects.

In addition, testing is an integral part of MSBE (Model Based System Engineering) to verify that models meet the requirements. Not only do the models of RoadRunner need to be tested, but the entire RoadRunner code base requires testing to satisfy software quality assurance requirements. A Jenkins server was set up to manage and launch the integration tests. At the end of each day, a set of integration tests is run to verify for various route scenarios through a testing framework including the functionality check (e.g., crashes, traffic light or stop sign run detection, over-speed limit detection or some vehicle stops without reasons). The tests produce an Excel report for a quick, high-level overview of each test with indicators of a pass or fail, and the detailed results from each simulation run, which can help diagnosis the cause of the failure.

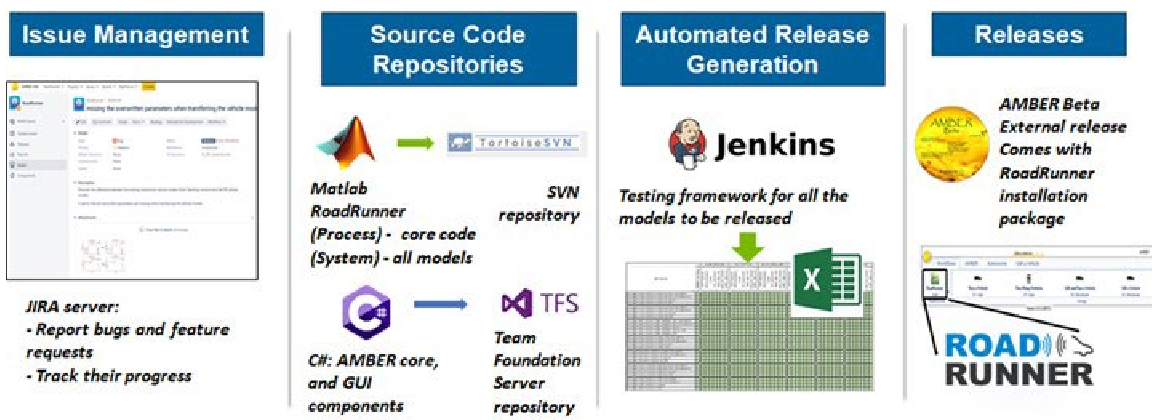

Figure I.3.2.2 RoadRunner part of AMBER's software development lifecycle

Improved human action model

We focus on the human action model that updates jerk (i.e., the derivative of acceleration) for capturing a dynamic car-following behaviors (rather than a way of avoiding rear-end collisions in [1]). The car-following is formulated as an optimal control problem (OCP) prioritizing driving comfort while maintaining the desired headway with the preceding vehicle. We reformulate and transform the original car-following OCP into a tractable car-following problem. Then, we derive analytical solutions and propose the computational-efficient and drivability-optimal car-following model. The proposed model, called analytical anticipative optimal drivability model (A2ODM), is also parametric to provide flexibility to create variety. To validate the proposed model, we post-processed and used Next Generation Simulation (NGSIM) US-101 LA highway data [2]. Results show that the A2ODM can generate stable car-following behaviors by precisely following the calibrated time headway in all ranges. Thus, its vehicle state trajectories are well matched with NGSIM data for a total of 524 vehicles, thereby significantly improving root-mean-square error of speed and distance gap on average over vehicles by 20% and 42%, respectively, compared to the existing car-following model, intelligent driver model (IDM), as shown in Figure I.3.2.3.

Figure I.3.2.3also shows trajectories of selected three validation vehicles by RMSE value (ID 301 – low, ID 8 – medium, and ID 567 – high). Both models generate collision-free trajectories but the IDM trajectory deviation from the data becomes greater when the vehicles maintain the longer desired time headway (e.g., ID 8 and 567). On the other hand, the A2ODM optimizes the boundary condition that corresponds to the preceding vehicle (PV) driving behavior in a predictive way so that it can maintain all ranges of the desired time headway and minimize its trajectory deviation from the data.

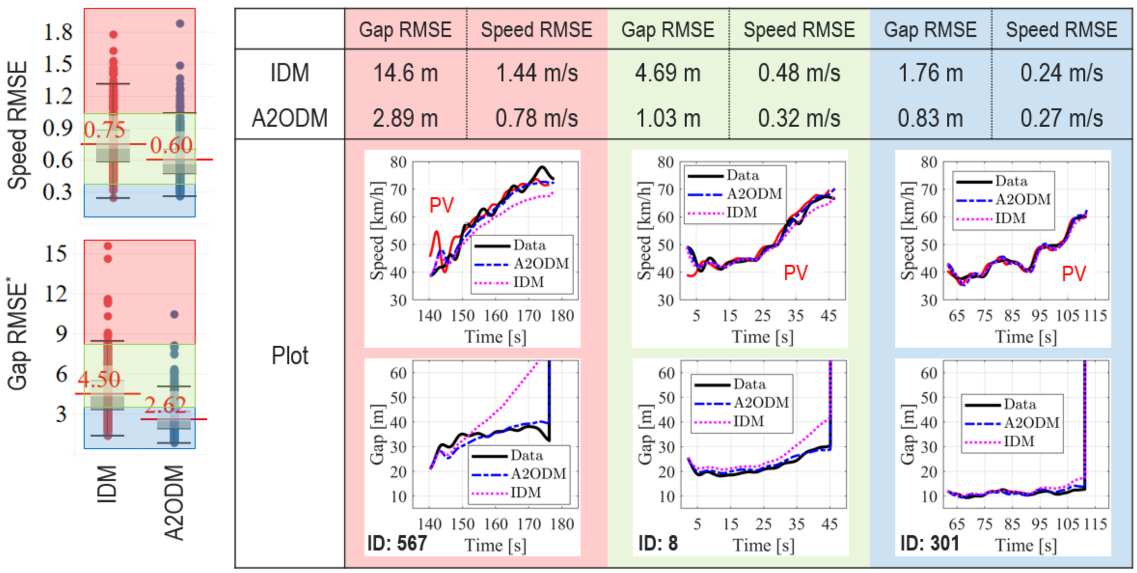

Figure I.3.2.3 Two model (IDM and A2ODM) comparison: speed and gap RMSEs for 524 vehicles (left) and trajectory deviation from data for selected three vehicles (right).

Data collection and analysis

Preprocessing the population description table

Hyundai created the population description table for a total of 11,268 customer vehicles that have the capability to collect and save data about the preceding vehicle (e.g., distance to preceding vehicle). We added geographical area attributes to the population description table by identifying the area defined by the U.S. Census polygon boundary [3] where the approximate home location is included.

- Legal/administrative areas: regions (e.g., Midwest), divisions (e.g., East North Central), and states (e.g., IL).
- Core based statistical areas (CBSAs) [4]: metropolitan statistical area (i.e., +1 urbanized area of +50,000 population), micropolitan statistical area (i.e., + urban cluster of between 10,000 and 50,000 population), and rural areas (i.e., no metropolitan and micropolitan areas).

Moreover, we defined the trip data requirements (e.g., 6 minutes ≤ mean daily average trip time ≤ 60 minutes) to ensure that vehicles have sufficient trip data and filtered out the undesired vehicles.

Stratified random sampling

The stratified random sampling method can divide the population into homogeneous groups, or strata, that are heterogeneous among themselves, based on predefined group criteria and randomly sample from each group in accordance with its predefined sample size. We applied this method to the preprocessed population description table. We defined group criteria using three influential factors such as vehicle type, CBSA type, and state for the stratification to minimize variability within the groups (homogeneity) while maximizing variability between the groups (heterogeneity). The stratification generated 166 groups comprising 7,247 vehicles and defined by seven vehicle types, three CBSA types, and 16 states, where the states are selected out of 44 using U.S. Census worker population data. We determined the sample size of each group using the following rules:

- All vehicles in non-metropolitan areas.
- Uniform allocation (same cluster size) over vehicle type clusters.
- Proportional allocation (different sample size) over groups included in each vehicle type cluster.

We used systematic random sampling to sample vehicles from each group population. This method is a probability sampling method in which vehicles are selected with a fixed selection interval from a random starting point. Depending on the selection interval type (equal or non-equal), every vehicle has equal or non-equal probability of being selected. We applied the non-equal selection interval defined by U.S. Census worker population data for large group sample sizes. This strategy enables large groups to have representative random samples for each state and the same distribution over metropolitan areas for different vehicle types.

Partially accepted data request and data processing on virtual server

Hyundai's data team was able to gather most of the data Argonne specified: a total of 1,875 vehicles across the United States, divided into 107 groups by four vehicle types, three CBSA types, and 16 states, as shown in Figure I.3.2.4. Hyundai hosted a virtual server to allow us to process the data. To this end, we developed Python routines to access the database and save the data vehicle by vehicle and improved the two high-level data processing algorithms (i.e., trip type identification and situation segmentation) to be more robust and capable of processing a large amount of driving data without issues. In summary, the processed data includes 63,517 trips, 1,052,902 km, and 22,902 hours of data.

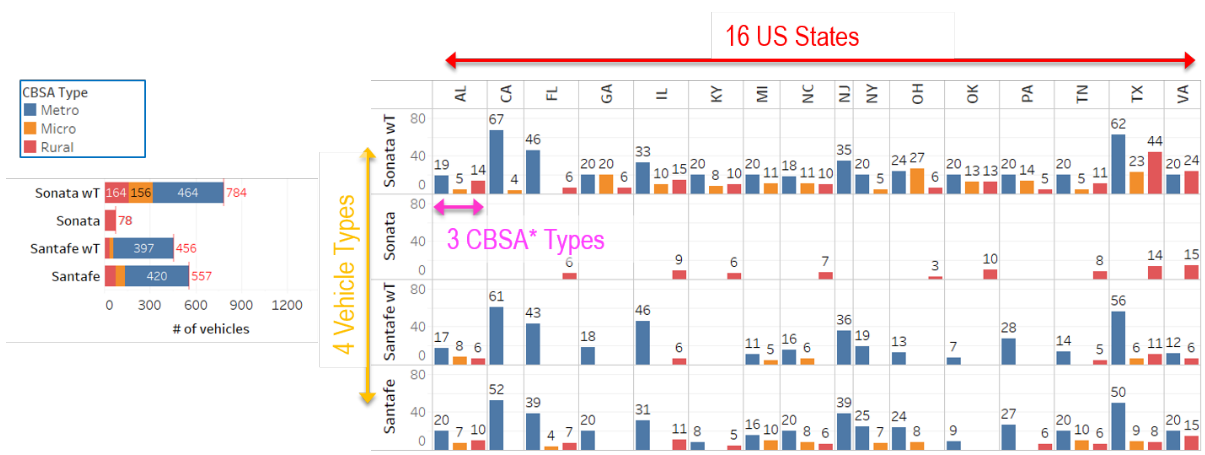

Figure I.3.2.4 Final list of vehicles of interests: total 1,875 vehicles in 107 groups

Preparation for on-road driving data collection

Hyundai finalized the instrumented vehicle setup for on-road testing based on Argonne inputs on data collection setup and quality after providing test data samples several times. To verify the video recording quality, we applied object detection algorithm [5], trained by DriveU Traffic Light Dataset (DTLD) [6], to the on-road test video images after pre-processing (e.g., focused area selection). Then, we extracted traffic signal status trajectory using the traffic light inference data (e.g., the traffic light status and confidence score).

In addition, we defined the first route to be tested by Hyundai (29 miles), which includes 87 intersections (81 traffic lights, five yields, and one stop sign) in urban and suburban areas in Ann Arbor, Michigan. Data collection should start in Winter 2021-2022.

Conclusions

The objective of the project is to bring RoadRunner—a tool dedicated to energy efficiency research in the context of advanced powertrain, connectivity, and automation technologies—closer to commercialization. In FY21 and as originally scheduled, RoadRunner was first released as a workflow in the AMBER Beta version with GUI including a road builder and a library of default vehicle models. Outside users can design and run a RoadRunner simulation case study by following step-by-step instructions with concrete examples. RoadRunner's maintenance and future updates will be facilitated by the integration of the tool within the AMBER software development lifecycle, ensuring the continuous high quality of the software. This part of the project—one of the main goals—is now completed.

The human driver model development and validation will be completed by the end of 2022 (due to COVID-related delays in data collection). In FY21, we used public datasets to continue developing the model. We developed the computationally efficient human action model for capturing the car-following regime with anticipation and showed trajectory accuracy improvement by 20% and 40% using NGSIM data in terms of speed and distance gap, respectively, compared to the IDM.

Further model development in FY22 will be greatly facilitated by the unprecedently large set of customer driving data that Hyundai provided to Argonne: one month of data for 1,875 vehicles and a total of 63,517 trips, 1,052,902 km, and 22,902 hours, with >30 signals at 1Hz. Furthermore, we coordinated with Hyundai regarding vehicle instrumentation and test routes for the on-road data collection.

In FY22, we will complete and apply the data analytics framework to customer data and on-road driving data to build a labeled driving dataset and perform the exploratory data analysis to find meaningful driving patterns as well as check assumptions on the influential factors (e.g., region). This analysis promises to offer insights into human driving behavior impacts of justified influential factors and help to explore the most appropriate P&D model. Finally, we will calibrate the human P&D model and integrate it with the action model to complete the Argonne human driver model and update the model in the RoadRunner library.

Key Publications

1. J. Han, D. Karbowski, and A. Rousseau, "Analytical Anticipative Optimal Drivability Car-Following Model," submitted to IEEE American Control Conference, Atlanta, GA, USA, June 8–10, 2022.

References

1. Han, J., Karbowski, D., Kim, N., and Rousseau, A. "Human Driver Modeling Based on Analytical Optimal Solutions: Stopping Behaviors at the Intersections." ASME. Letters Dynamic Systems Control. January 2021; 1(1): 011010.

2. U.S. Department of Transportation Federal Highway Administration, "Next generation simulation (NGSIM) vehicle trajectories and supporting data," https://data.transportation.gov/d/8ect-6jqj.

3. U.S. Census Bureau. Cartographic Boundary File. Accessed from https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html.

4. U.S. Census Bureau. Metropolitan and Micropolitan. Retrieved 2019. Accessed from https://www.census.gov/programs-surveys/metro-micro.html.

5. Joseph Redmon, Santosh Kumar Divvala, Ross B. Girshick, and Ali Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779–788, 2016.

6. Andreas Fregin and Julian Müller and Ulrich Krebel and Klaus C. J. Dietmayer, "The DriveU Traffic Light Dataset: Introduction and Comparison with Existing Datasets," 2018 IEEE International Conference on Robotics and Automation (ICRA), pp. 3376–3383, 2018.

Acknowledgments

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I.3.3 MEP- A Customizable Metric to Quantify the Quality of Mobility (NREL)

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Start Date: April 1, 2021
End Date: March 31, 2023
Project Funding: $886,149
DOE share: $438,149
Non-DOE share (in-kind): $448,000

Project Introduction

An ideal future is one which citizens can be well-connected to goods, services, employment, and each other in an energy efficient manner. Many new transportation technologies are enabling significant progress towards such a vision. Consequently, fast-paced decision-making for transportation practitioners is necessary and increasingly challenging due to a lack of knowledge regarding mobility-energy tradeoffs from many new and developing technologies. In this new era, older roadway-infrastructure methods of measuring transportation system efficiency are falling short. Measures such as vehicle miles traveled, miles per gallon, travel time, and congestion are unidimensional and fail to capture true mobility. While there are many metrics to quantify energy efficiency, mobility has proven elusive to quantify objectively. Often, access-related metrics focus on a single mode (e.g., walking) or a single need (e.g., access to jobs). Addressing these needs, researchers at the National Renewable Energy Laboratory (NREL) have developed a novel and practical method to quantify the mobility potential of a region. Labeled the 'Mobility Energy Productivity Metric (MEP),' the MEP provides a means to quantify mobility within energy and productivity contexts to inform planning decisions towards better energy productivity. While initial iterations of the MEP methodology have been applied in isolation to various cities in the United States, developing a commercialized product that helps cities develop a baseline of their mobility potential and continually monitor its progress will be invaluable for planning and decision-making purposes. The data required to feed such a comprehensive metric has only started to become available in the past decade. Partnering with Street Light Data (SLD)—a leading urban mobility data analytics firm—the end goal of this proposal is to produce a commercial version of the MEP metric.

Objectives

The objective of this project is to develop the MEP metric for use as an urban mobility planning tool by leveraging data available through our industry partner and preparing a customizable MEP implementation for integration into SLD analytics. The project plan is divided into three tasks.

- Task 1 of the project will focus on data identification, code enhancements, and development of a web prototype to deliver MEP results.
- Task 2 of the project will concentrate on demoing the protype to various stakeholders and soliciting feedback.
- As a part of Task 3, MEP calculations and the enhanced web prototype will be delivered to two cities chosen as a part of this project. At this stage, SLD will be provided with a choice to integrate the MEP visualization package into their product deployment environment or market as a standalone product.

As a commercialization project, this project is as much reliant on stakeholder engagement and feedback as it on the technical and methodological effort.

Approach

The first phase of the project will deal with identifying and acquiring robust and perennial data streams to compute the MEP metric along with any necessary methodological refinements to facilitate these needs. This phase will also focus on forming a steering committee, comprising of representatives from MPOs, planning organizations, and advocacy groups to review project work, and offer suggestions on MEP formulation, needs, and visualizations. The steering committee will meet quarterly via conference call, be given access to project material and results, and be solicited for detailed feedback. The first technical task on the project is to perform a data inventory, charting necessary data to support a nationwide rollout of the MEP, mapping various data set attributes to requirements, and noting cost, license, and other restrictions of use. The key data elements used in the computation of the metric are network speed data; land use data; energy efficiency measures; travel demand data; and cost measures.

Subsequently, in the first phase of the project, MEP methodology will be enhanced to introduce mode-activity realism when computing the metric for specific mode and activity combinations. The project team has already made some progress on this (as a part of a parallel SMART 2.0 project) and is confident that these can be rolled in with low-level effort into the MEP TCF project. Another effort that will be undertaken in conjunction with the SMART 2.0 MEP project is the development of an elegant and efficient web visualization prototype to display the results of the MEP calculation for a city. A preliminary version of the web visualization is developed as a part of FY21 efforts. Parallel to this effort, procedures will be set in place to compare the MEP scores computed for various locations in the city with other related metrics.

Results

Steering Committee: Working with the industry partner (SLD), a steering committee (shown in Table I.3.3.1) was formed in August 2021 to guide the MEP TCF project.

Table I.3.3.1 MEP TCF Steering Committee

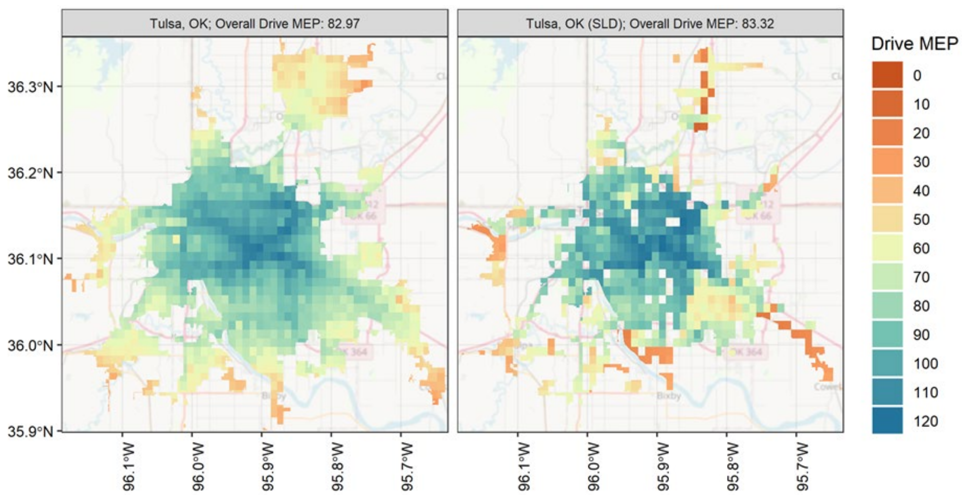
Name (Position)	Organization	Organization Type
Nick Lepp (Director of Transportation Planning)	Metroplan Orlando	MPO
Nimish Dharmadhikari (Transportation Modeling Coordinator)	Indian Nations Council of Governments	MPO
Chris McCahill (Deputy Director)	State Smart Transportation Initiative University of Wisconsin-Madison	University
Annalisa Schilla (Chief, Community Action Branch)	California Air Resources Board	State Entity
Morgan Ellis (Vice President of Sustainable Transportation)	ITS America	Advocacy Group
Heather Croteau (Technology Manager, Energy Efficient Mobility Systems Department of Energy)	Department of Energy	Federal Govt.

MEP Calculations: SLD has made the following network data for Tulsa and Orlando available to NREL.

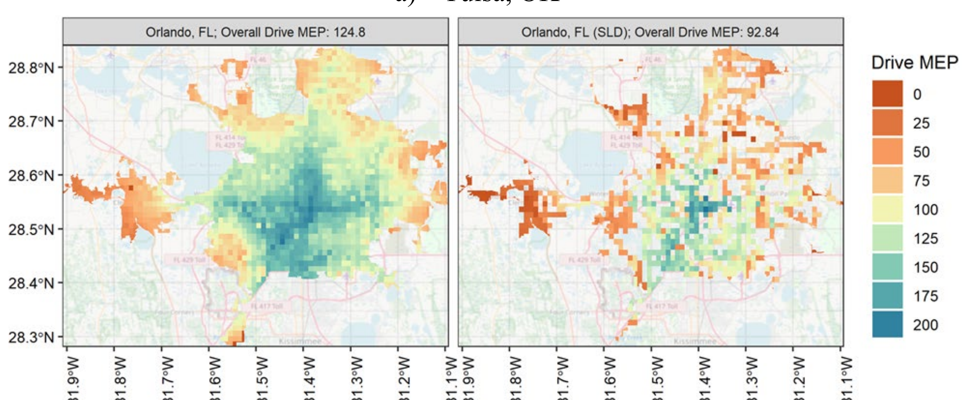
- **Geographies**: Tulsa MPO and Orlando MPO Counties plus 40-mile buffer

- **Open Street Map (OSM) Network**: 500-meter split network
- **OSM Segments**: Tertiary and up (residential streets can be delivered but with no metrics)
- **Data Period**: All of 2019
- **Day Type**: Weekday (Monday – Thursday), Weekend (Saturday – Sunday), All Days (Monday – Sunday)
- **Day Part**: AM Peak (6 – 9 am), Afternoon (11 am – 2 pm), PM Peak (4 – 7 pm), Off-Peak (11 pm – 2 am)
- **Metrics**: 50% and 85% Percentile vehicle speeds.

The current network information used in MEP calculation is replaced with SLD data. The MEP comparisons based on standard network data as well as SLD provided network information can be seen in Figure I.3.3.1 (a) and Figure I.3.3.1 (b) for Tulsa, and Orlando respectively.



a) Tulsa, OK



b) Orlando, FL

Figure I.3.3.1 MEP comparisons based on standard network data as well as SLD provided network for a) Tulsa, OK, and Orlando, FL.

From the results, it can be observed that MEP scores for a few pixels in the SLD MEP calculation came out to be zero, whereas these pixels had non-zero scores in the original MEP calculation. This could be due to the following reasons:

- SLD network is a simplified version of Open Street Maps (OSM). Many bi-directional links in the network are incorrectly coded as unidirectional, resulting in reduced access where such links exist.
- SLD only provided data for freeways and arterials. Links pertaining to minor and/or local roads are missing. Sparser network can lead to misrepresentation of access to destinations.

SLD is looking onto both these issues, and plans to send updated networks for Tulsa, and Orlando soon.

MEP Web Visualization: A beta-version of the MEP web visualization prototype is developed (in conjunction with the visualization task in SMART 2.0). A snapshot of the visualization tool is show in Figure I.3.3.2.

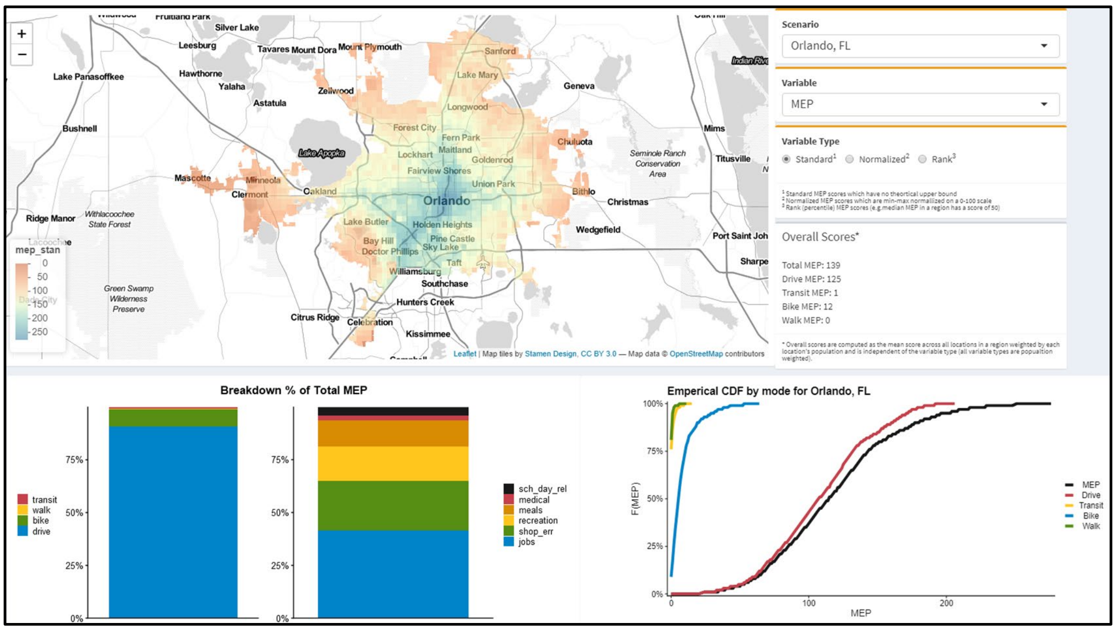


Figure I.3.3.2. Protoype of the MEP visualization tool.

Through the tool, the end users will have the ability to view standard (unscaled) MEP scores, or normalized as well as ranked versions of MEP scores. In addition to the spatial visulaization of MEP scores, the tool will also provide mode-wise and activity-wise summaries of MEP scores.

Conclusions

In the first few months, the project team focused on

- Forming a steering committee
- Carrying out a preliminary MEP calculation based on SLD provided network data
- Developing a beta-version of the MEP visualization tool.

In the next fiscal year, the team will

- Explore OSM Point of Interest (POI) as a potential replacement to land use data currently used on MEP calculations

- Identify independent metrics that MEP can be compared with
- Have discussions with SLD regarding the data required and level of effort involved in computing MEP score for a city. This will help SLD come up with a cost estimate they can share with potential customers in the latter part of the fiscal year.

Acknowledgements

From the PI: The PI would like to acknowledge Chris Hoehne's efforts in calculating MEP scores based on SLD data, and in developing the beta-version of the MEP visualization tool.

From the Project Team: The project team would like to extend their sincere thanks to EEMS technology manager Heather Croteau for her regular feedback on the TCF project.

I.3.4 Virtual and Physical Proving Ground for Development and Validation of Future Mobility Technologies (Oak Ridge National Laboratory)

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Start Date: October 1, 2018 End Date: December 31, 2021
Project Funding (FY20): $1,150,000 DOE share: $1,150,000 Non-DOE share: $0

Project Introduction

Emphasis on pushing the state of the art of advanced transportation technologies, specifically connected and automated vehicles (CAVs), has recently gained significant momentum in both government and industry. The Department of Energy's SMART Mobility program is attacking the "transportation as a system" problem from multiple angles. Therefore, modeling, simulation, and analysis form the backbone for future prediction of the impacts of various technologies on mobility for the nation, in the form of the Mobility Energy Productivity (MEP) metric. A need has been identified to experimentally evaluate these solutions to ascertain the validity of their respective claims, as well as to generate critical data to feed back into SMART Mobility–developed tools for more detailed analyses. An advanced hardware-in-the-loop (HIL) platform capable of bridging the gap between analytical models and real-world hardware provides the intermediary to identify the most promising technologies that should be fully verified at the vehicle system level.

Model-based design has become the industry standard for developing vehicle supervisory and powertrain control systems. However, this approach misses the complexity of the interactions of physical hardware in real-world driving conditions. The novel approach proposed by ORNL advances the state-of-the-art research by exercising actual hardware in real-world traffic situations, in which the vehicle is expected to be operated, to capture the subtle effects of communication timing/latencies, actual powertrain energy consumption, emissions, and other dynamic phenomena. The ability to subject actual hardware to simulated real-world conditions allows diverse scenarios to be simulated for enhancing strategies and algorithms, as well as responding to micro- and macro-level traffic environments that current high-level traffic network models fail to capture. In addition, this framework provides a repeatable, cost-effective environment for rapid development and validation of CAV technologies, including their respective vehicle controls and communication protocols. This capability offers the benefit of absolute safety since the control algorithms are evaluated thoroughly in a controlled HIL laboratory environment before being targeted to an actual test vehicle for on-road or track testing.

Objectives

The objective is to accurately verify the energy benefits and emissions impacts of these advanced technologies with actual powertrain hardware physically installed in the laboratory and subjected to virtual traffic conditions for research. This approach presents the opportunity to research, develop, and evaluate a large matrix of CAV technologies over a greater, customizable design space at a time when vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) hardware has not even been completely developed or is not available for full-scale testing.

ORNL will investigate early stage "smart" technologies as a system, regardless of the powertrain architecture or actual physical design selected by the researchers. Multiple research facilities within ORNL will be virtually connected to develop a novel and flexible approach to examine multiple hardware components in a variety of powertrain configurations and traffic environments in real-time, high-fidelity, traffic simulations while subjecting actual powertrain(s) to emulated real-world traffic conditions. This approach will allow for the development of control strategies and algorithms specifically targeted at advanced vehicle technologies, as well infrastructure controls.

Approach

Task 1: "Virtual-Physical" Proving Ground (VPPG)

Considering VTO's efforts to tackle difficult questions regarding current and future smart vehicle technologies and their impact on mobility, the EEMS program and SMART Mobility consortium are trying to analyze many different CAV and SMART Mobility technologies to identify the most promising and efficient methods for future transportation and corresponding infrastructure. This work has highlighted a real need for cross-collaboration among different scientific skill sets to produce a well-analyzed and validated answer that starts in modeling and simulation and ends in validated HIL and vehicle-level laboratory experiments. This end-to-end process provides data to improve the modeling activities. ORNL is addressing this need by bringing together its various skill sets for use in the Virtual-Physical Proving Ground.

Subtask 1.1: Standardized Virtual Proving Ground Framework

The goal of Task 1.1 is to allow flexibility in creating combinations of modeling, simulation, HIL, and vehicle-level testing. This task focuses on establishing a standardized framework that allows for the integration of multiple HIL -based research capabilities within ORNL, as well as provisions for connectivity with other national laboratory facilities, tools, and capabilities. This will allow for greater flexibility and for ease of integrating required formats, including macro traffic simulations and high-fidelity vehicle environment simulations. This flexibility to integrate many different modeling and simulation software is an important aspect of Task 1.1 because of the many different DOE tools that are being developed by DOE laboratories, as well as industry tools already in use both within the DOE laboratory system and by industry partners. Once the framework is completed, ORNL will begin to integrate a small selection of EEMS and/or SMART Mobility tools and data sets into a verification tool and as a high-fidelity data collection effort for more robust, validated models as part of subtask 2.3. Data will be collected by a fully instrumented RAV4 mule vehicle on Bethel Valley Road at ORNL's main campus. Then, ORNL's digital twin of the main campus will be used to replicate the scene and traffic experienced by the test vehicle on the real road. Lastly, the ORNL RAV4 mule vehicle that drove the real route will be deployed in the CAVE lab to virtually drive through the digital twin of Bethel Valley.

Subtask 1.2: Scenario Based Testing/Validation for Advanced MD Delivery Vehicle

The Automotive industry has used standard timeseries based duty/drive cycles for many years and are well understood and mature. These drive cycles are good for certification testing, but often lack the detail and interactive nature required to be a better analog to real-world driving and scenarios. Utilizing an advanced range extender battery electric powertrain, this task will develop and test the powertrain in multiple scenarios and traffic densities on realistic road networks generated for real interstates and arterials.

Subtask 1.3: Virtual Proving Ground Applied to Open-source tools

While commercial simulation tools are often more feature rich, further developed, and user friendly, they are extremely expensive and often less flexible than their open-source counterparts. Due to the expense and flexibility, open-source tools are often favored by academia, research institutions, and national laboratories. Once ORNL has integrated its current selection of commercial virtual environment simulation tools (IPG Car/TruckMaker, dSPACE ASM, VIRES VTD, and PTV Vissim) into the VPPG, the team will then begin to integrate a selection of open-source tools into the VPPG as well. The three packages are CARLA (an open-source virtual environment), SUMO (an open-source traffic microsimulation), and ROS/Autoware (an open-source perception and control stack). Once these links are established, ORNL will then utilize them in a laboratory setting to work out any real-time or HIL concerns with these very new and flexible software packages. This is critical as open-source software packages often have bugs associated with strict computation time steps. Once this task is complete it will be applied to the SMART Mobility project within Subtask 2.3.

Task 2: (V2X) Communication Modeling, Development, and Validation

Currently, V2V, V2I, and other vehicle communications (V2X) are in their infancy. What final V2X infrastructure and capabilities look like is an ever-changing landscape. This situation emphasizes the need for development and testing platforms that are extremely flexible, programmable, and able to go back and forth from the modeling/simulation space to real hardware testing. ORNL's VSI Laboratory, Vehicle Research Laboratory, and CAVE Laboratory are extremely well suited for fulfilling this need. With the virtual vehicle environment established in Task 1, V2X hardware will be tested while tied to a virtual vehicle in a real-time HIL environment or can be tied to an entire vehicle or powertrain in the test cell. This testing is all done in an extremely flexible environment that allows for low- to high-fidelity data streams, quick programming changes, and repeatable laboratory results.

Subtask 2.1: Integration of V2X Communications Hardware into Virtual Proving Ground Framework

Subtask 2.1 enhances the Virtual Proving Ground with a communications-focused testing platform consisting of multiple V2X communication hardware development units integrated into several ORNL vehicle test facilities and HIL-enabled test facilities such as the VSI, CAVE, and Vehicle Research. The Vehicle Research Lab is a traditional chassis dyno lab that is used for fuels and emissions work that will be added to the network of systems, so two full vehicles could run in the loop. This approach enhances the overall Virtual Proving Ground capability with the ability to understand V2X hardware integration, communication, latency, controls delays, reliability, interference issues, and so on. This is achieved either through virtual communications or physical communications depending on lab proximity. For instance, the Vehicle Research and Security laboratories are within physical communications distance, but the VSI laboratory is not and must rely on a virtual link.

Subtask 2.2: Light-Duty Virtual Proving Ground for V2X Evaluation

As a means of proving the capability established in Task 2.1, the team will collaborate with the American Center for Mobility (ACM) staff. The objective of Subtask 2.2 is to replicate "virtual versions" (i.e., digital twins) of the ACM facilities and communications network so that CAV technologies and control strategies can be quickly and easily verified in a safe, secure setting before vehicle deployment. Since actual vehicle components will be exercised through modeling, simulation, and HIL approaches, a full understanding of the expected energy and communications impacts can be achieved. These enhancements to the digital twin will allow this project's communication models, hardware, and degradation experiments to be verified at ACM in collaboration with the ACM Model Validation project. Working closely with ACM staff, the approach presented here can cost effectively expand the possible design space of new and emerging technologies with a higher degree of accuracy (due to HIL principles) while providing insight into test plan development for full vehicle/system testing. Specifically, the utilization of the virtual replica of ACM facilities allows for current and future co-development and targeted, preliminary testing that optimizes scenario definition and track usage. Utilizing the work done in Subtask 1.3, the replicated communications network will also be integrated with CARMA modules like the ones used by ACM to allow the ORNL mule vehicle to communicate with the virtual roadside units mirroring ACM's layout.

Subtask 2.3: Connected Laboratory Coordination Testing

As a part of the DOE SMART Mobility 1.0 consortium, ORNL has developed an approach for optimizing CAV control and coordination. This modeling framework can be adapted to different traffic scenarios and can be used in a real-time system, given its analytical, closed-form solution. The approach taken to coordinate vehicles has been used to assess the impact of full penetration of optimally coordinated CAVs across different traffic scenarios. Applying this concept to vehicle HIL can validate the fuel-saving trends that have been found through simulation and/or provide feedback for model development. To this end, actual V2X communication, between the vehicles located in various ORNL HIL laboratories and a central coordinator, will improve a real-time optimal merging coordination algorithm. A chassis dynamometer (CAVE lab) and HIL components will interact through a traffic simulation with virtual vehicles. All the "vehicles" will receive control inputs from the centralized coordinator according to the optimal controller computations. The vehicles and powertrains located in the various HIL dyno laboratories will be operated by both real and virtual drivers that will follow the instructions given by the central coordinator. A minimum of two laboratories will be connected in this testing, but more can be added depending on project resources.

Results

Subtask 1.1: Standardized Virtual Proving Ground Framework

The CAVE Lab needs additional tire dynamics and 3D visualization environment to fully evaluate an ego vehicle, which requires integration of a tool such as IPG CarMaker, CARLA, dSPACE ASM. IPG CarMaker is simulated on a host PC and communicates with the dyno and the CAVE Lab vehicle in real-time as shown in Figure 1. The integration of IPG CarMaker with the CAVE Lab provides a complete solution and can represent AV sensors as well as the ego vehicle with high fidelity. On one hand, the IPG CarMaker visualizes the 3D environment of the driving scenario as well as simulates the AV sensors, tires, and vehicle dynamics. On the other hand, the CAVE Lab consists of the human driver or automated vehicle controller and the actual powertrain dynamics. As a demonstration user case, the CAVE Lab vehicle is driven in the ORNL digital twin. ORNL's fully instrumented RAV4 mule vehicle was driven to collect vehicle data on Bethel Valley Road at ORNL's main campus also shown in Figure I.3.4.1. This data recorded of ORNL's main campus will be compared to the digital twin of the main campus and will be used to replicate the scene and traffic experienced by the test vehicle on the real road. Lastly, the ORNL RAV4 mule vehicle that drove the real route will be deployed in the CAVE lab to virtually drive through the digital twin of Bethel Valley Road.

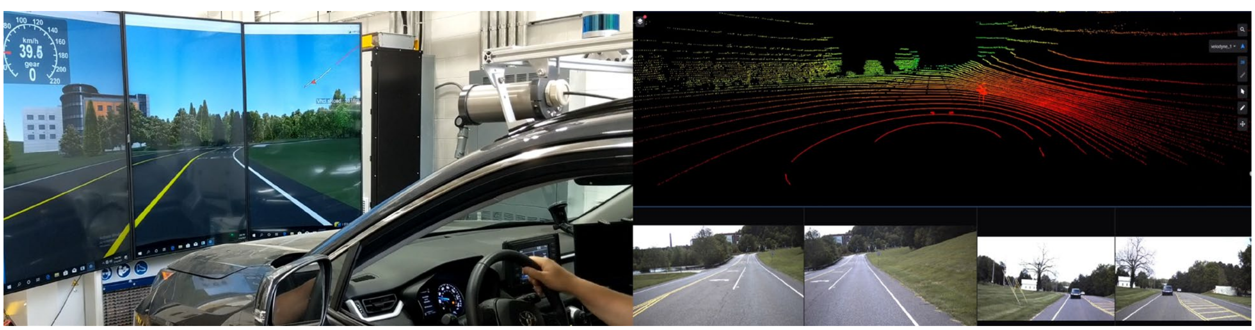

Figure I.3.4.1 Left - RAV4 vehicle mule in the CAVE implementation of IPG on the digital twin of the ORNL campus, Right - Screen shot of on-road data taken from vehicle mule on ORNL's main campus.

The flexible interface is implemented in a Server-Client fashion and the coupling between each component is through network communication protocol TCP/IP. Therefore, it is fully modular and flexible and can be used to integration various vehicle and traffic simulation tools, and XIL components. Figure I.3.4.2 shows the upgraded overall architecture of the interface. There are two major components: 1) Traffic Layer, which is the core that directly connects to the traffic simulator to extract traffic information; 2) Application Layer, which holds the programs that enable CAV application. Traffic Layer acts as a "Server" that distributes the traffic information to all connected "Clients", Application Layer, and does not need to have any information about how "Clients" will use the information. Each "Client" only needs to subscribe to the information it is interested in (details are given in the "Message Flow" section). "Client" is essentially the Application Layer that holds the CAV algorithms. It receives the traffic information and further processed to generate the control commands for the CAV Application Clients, which can be ego vehicle simulators, HIL testbeds, physical signal controllers, etc. Depend on the specific CAV application, the Application Layer could be applied in either the centralized scheme or distributed scheme. In the centralized scheme, a single Application Layer is used which contains a centralized controller that determines the control commands for e.g., all ego vehicles, and passes the commands to the CAV Application Clients. This centralized Application Layer essentially acts as the "Server" to all CAV Application Clients. Each "Client" subscribes to the "Server" to receive corresponding control command, and the "Server" has no need to know the details of the "Client". This modular design facilitates integration with different vehicle simulators and XIL testbeds for various applications. In the distributed scheme, each CAV Application Client is tied with one Application Layer. Each Application Layer only holds the control strategy for the corresponding CAV Application Client. The Traffic Layer is then connected to multiple Application Layers where each subscribes to only information in proximity. The same Application Layer program can be applied to both centralized scheme and distributed scheme. The only difference is the number of connected CAV Application Client and the subscribed information. The "Example Applications" section demonstrates the actual implementation of this ORNL Interface in two cases.

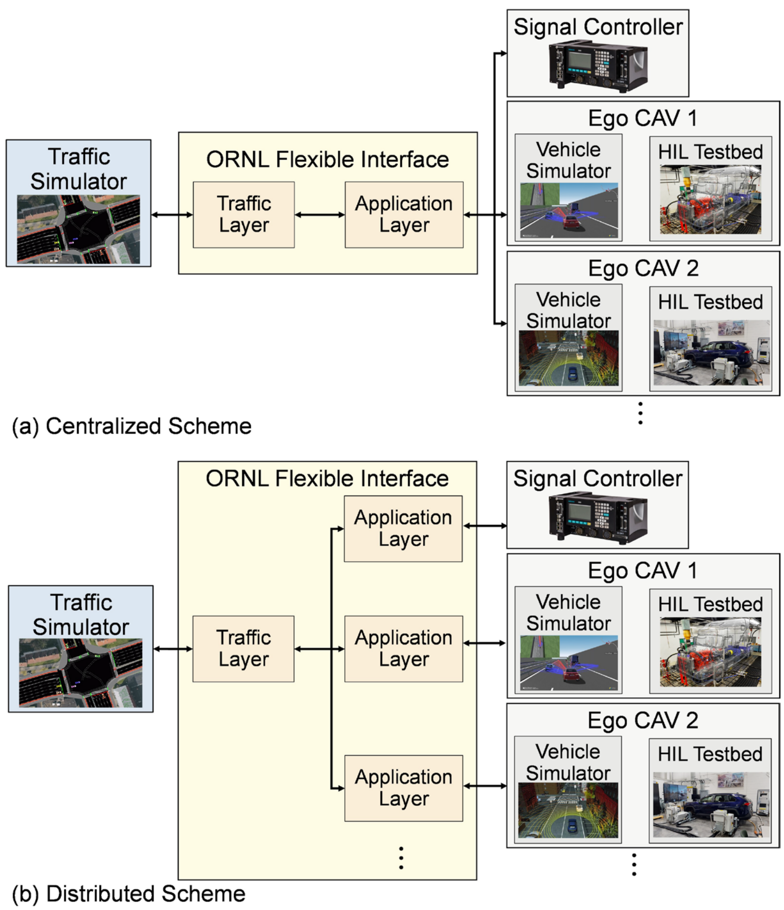

Figure I.3.4.2. Upgrades to flexible interface to allow for centralized and distributed/decentralized supplications.

Subtask 1.3: Virtual Proving Ground Applied to Open-source tools.

Significant progress was made developing a framework for integrating high fidelity Simulink models into the CARLA environment. The Simulink model is responsible for modeling the vehicle up to the contact patch of the tire, while CARLA simulator handles the contact patch of the tire and contains the virtual driver. Positional information (X, Y, Z) and rotational commands (roll, pitch, yaw) are calculated in the Simulink model based on the feedback from CARLA's tire model and driver (Wheel Angle, Accelerator & Brake, Friction Coefficient) as show in Figure I.3.4.3. In its current configuration, this is longitudinally functional (no steering). Some additional integration work with CARLA's custom functions need to be flushed out to add

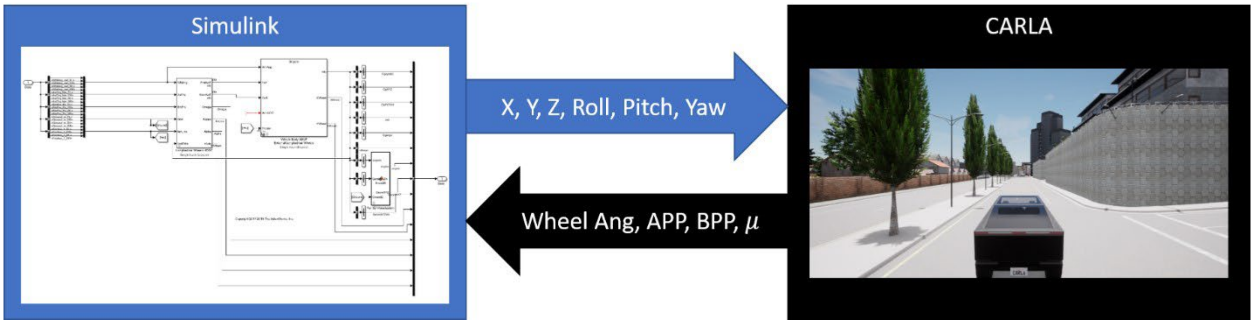

Figure I.3.4.3. Flow chart of vehicle dynamics and control from Simulink model to CARLA.

lateral control. Following some additional calibration, this integration between Simulink and CARLA will be competed.

Subtask 2.3: Connected Laboratory Coordination Testing.

Real-time connected lab testing has been conducted for a cooperative merging scenario for connected and autonomous vehicles. This enables multiple HIL systems running at the same time to simultaneously evaluate multiple ego vehicles. Figure I.3.4.4 shows the overall diagram of the connected lab interface. Two dSPACE HIL systems relate to SUMO traffic simulation running on a host PC with a cooperative merging algorithm communicating through TCP/IP. As opposed to the simulations with IPG and the CAVE lab, both dSPACE systems run a complete vehicle and powertrain Simulink model to simulate high-fidelity vehicle dynamics. One dSPACE and associated vehicle model represents an ego vehicle on the main road, while the other one represents an ego vehicle on the merging road. The requested vehicle speed of each agent is controlled by the centralized controller, while the driver model in each of the two vehicle models is responsible for meeting the requested speed. In each scenario, the vehicles are brought into the simulation at a constant speed, then the speed commands from centralized controller are enabled once they reach the control zone. Note that this approach does only constrain future development outside of SUMO and can also be extended to other tools such as VISSIM.

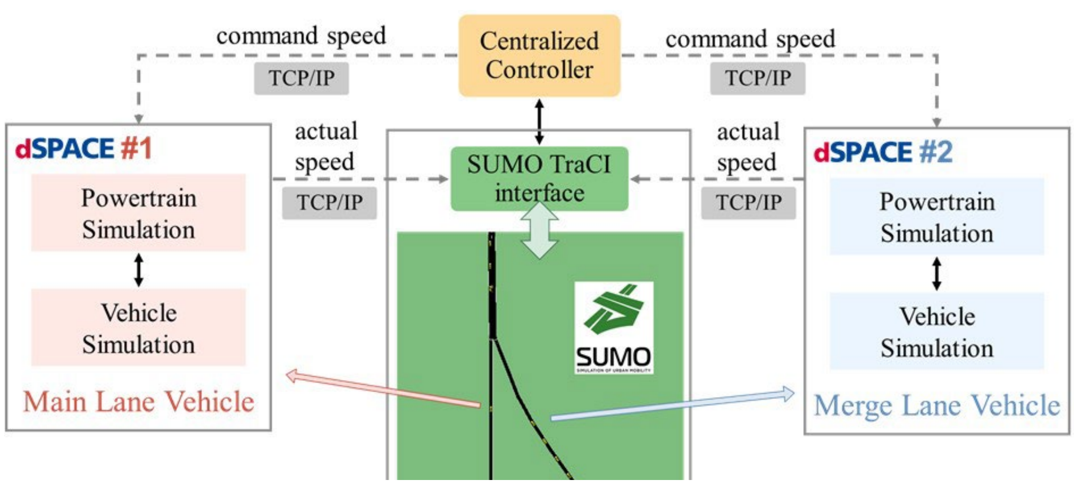

Figure I.3.4.4. Diagram of the connected lab architecture and communication.

The two dSPACE systems, SUMO and centralized controller require time synchronization every 0.1 seconds. This is also the control step of the centralized controller and simulation step of SUMO. However, the dSPACE systems and the models executing on them run at a higher 1 millisecond time step and execute in real time. Figure I.3.4.5 shows the diagram of the synchronization mechanism. At every 0.1 seconds, the actual speed is sent from dSPACE to SUMO to update the ego vehicle speed and run 1 step (0.1 seconds) of traffic simulation. The centralized controller receives the updated traffic information and calculates the ego vehicle's speed command at the next 0.1 seconds and send back to dSPACE. The dSPACE interpolates the speed until the next 0.1 seconds. Before receiving this speed, the previous speed command is hold and used. With this

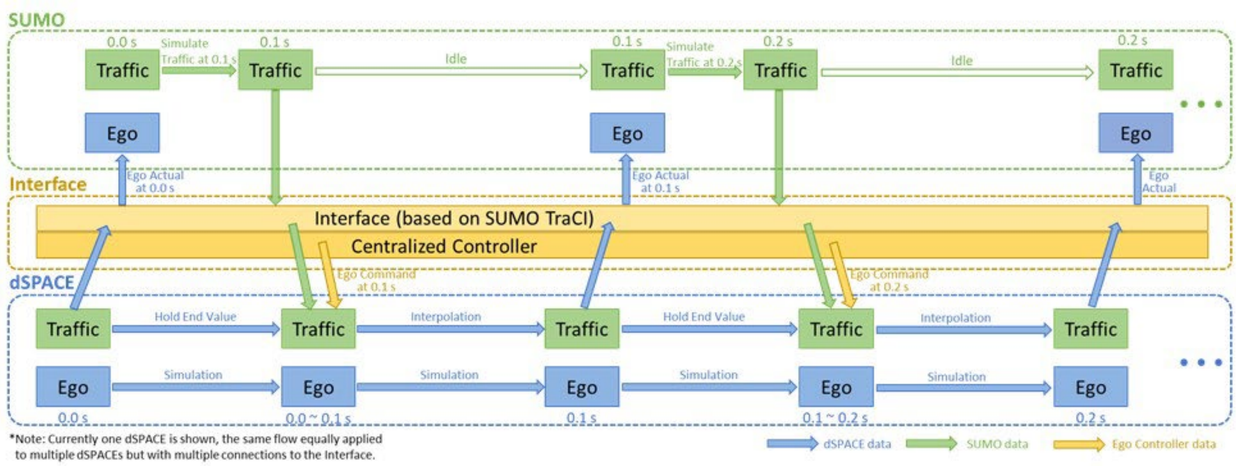

Figure I.3.4.5. Diagram of the synchronization mechanism utilized for connected lab operation.

setup, dSPACE and SUMO will be synchronized and have the same speed command at every 0.1 seconds time step. The total cost of coordination is 30-60 milliseconds which is well within 0.1 seconds. The SUMO simulation and centralized controller cost is 10-20 milliseconds, the communication cost of TCP/IP is 20-40 milliseconds.

Conclusions

The Flexible ORNL interface, integration, and simulation has made major strides in the last year even with delays that were incurred from COVID. However, the laboratory work has suffered many delays due to the lack of staff on-site and resources to get physical setups changed and installed to support this project as well as others. The project has been extended to December 2021 to finish the laboratory portions of the project. With this extension the VPPG will be exercised in two to three applications as talked about in the approach for subtasks 1.2 and 2.3.

Acknowledgements

ORNL would like to thank David Anderson, Erin Boyd, and Danielle Chou as the DOE EEMS Program Manager and Technology Managers, respectively and their continued support on this project.

II Connectivity and Automation Technology

This chapter contains project summaries that address Connectivity and Automation technologies. The EEMS Program's Connectivity and Automation Technology R&D portfolio focuses on innovative, early-stage, and scalable mobility projects and targeted system-level opportunities to reduce the energy intensity of the movement of people and goods through connected and automated 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.

II.1.1 Developing an Energy-Conscious Traffic Signal Control System for Optimized Fuel Consumption in Connected Vehicle Environments

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Start Date: October 1, 2020 End Date: December 31, 2023
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 connected vehicle (CV) 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 (UCVs)] along a corridor through capitalizing on emerging CV and CI communication technologies, as well as opportunities created by recent advances in Artificial Intelligence (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 Adaptive Traffic Control System (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. We will design and implement data-driven algorithms, first validating the proposed system in simulation environment and ultimately field testing along a 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 communication technologies 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 and 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-ETCS.
- Validate the developed algorithms using advanced simulation & modeling techniques.
- Demonstrate the developed technologies and algorithms through field testing.

Results

Data Infrastructure

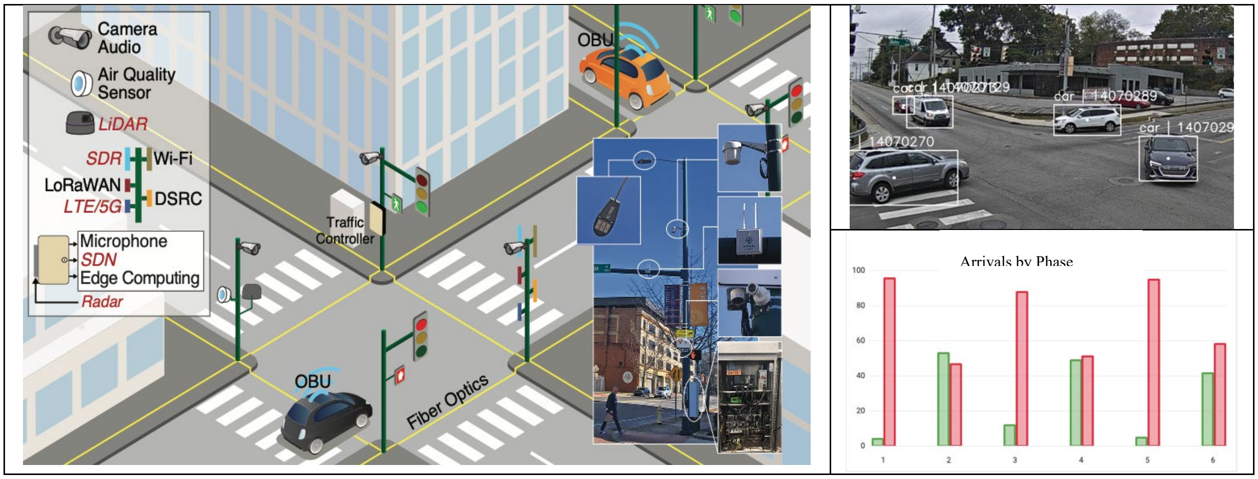


Figure II.1.1.1 Image of one of the intersections of the MLK Smart Corridor in downtown Chattanooga, TN; detecting, and labeling objects using AI-based computer vision; and sample of existing percentage of vehicles arriving on red and green

For Eco-ATCS data from heterogenous sources such as current and predicted traffic states at intersections, signal phasing and timings (SPaT), intersection CAD files, and vehicle specific attributes is needed in a low-latency and reliable fashion. The real-time and historical data are originated from the MLK Smart Corridor testbed in downtown Chattanooga, TN shown in Figure II.1.1.1. Our team has designed and implemented a data architecture based on four design considerations: low-latency, reliability, schema agnostic and high-availability. Low latency: Eco-ATCS relies on high-frequency data to make decisions. For example, if the prediction results are not provided within the time constraints the actions proposed may be optimal for a state that has already passed. The infrastructure utilizes three principles in the protocol implementation: batching, zero-copy, and non-blocking IO, to reduce communication latency. This protocol takes advantage of zero-copy which allows data to be copied directly from the operating system page cache. This also eliminates all CPU cycles needed to copy the data. Reliability ensures that each message is delivered at least once and no more than once. Duplicate communications can incorrectly describe the state of the system resulting in poor decision making. Exactly once schematics is accomplished through transaction acknowledgement strategies. These strategies provide bi-directional communication between the client and server. The server contains a coordinator agent that monitors the success and failures of data deliveries. During a failure, the coordinator rolls back the version of the data to the previous state. Once the state rollback is complete, the server requests redelivery from the client. As more data sources are being available or needed, the data infrastructure needs to be adaptable to new data sources, their format and size by being schema agnostic. High availability ensures an agreed level of operational performance, usually uptime, for a higher-than-normal period. Traffic signals are operationally critical to regulate traffic flow, improve congestion and reduce emissions. While traffic signals provide a fallback method for offline operations, downtime should be reduced to a minimum. The adopted architecture provides high availability inherently as a distributed system. Data is replicated across nodes so we can ensure that even if a node goes offline, we can ensure that all data requests are fulfilled.

Eco-PI metric for fuel consumption and vehicular emissions optimization

Fuel consumption (FC) and achieving energy efficiency through traffic management have been long-standing goals of the traffic research community. Although there is a good number of performance measures that are used to characterize operations of traffic signals, a trend of developing new traffic signal performance measures has especially strengthened after the emergence of a new methodology to retrieve high-resolution (10 Hz) detection and signal data. Our team has developed Ecological Performance Index (Eco-PI), an environmental-based objective function for control optimization. The Eco-PI is a performance measure that characterizes impact of signal timings on excessive FC and vehicular emissions at signalized intersections by looking at how various operational and traffic conditions impact unnecessary stops at controlled intersections. Eco-PI is a scalable performance measure that can be estimated on various spatial levels—from an Eco-PI for a specific traffic movement (related to a signal phase), through an Eco-PI for a whole intersection (to be able to find right balance for various traffic movements), to an Eco-PI for the entire road network.

The main performance measures for Eco-PI estimation are delay (d_{m_i}), number of stops (N_{m_i}) and stop penalty (K_{m_i}) which need to be estimated per movement (m) of each intersection (i). Thus, Eco-PI is defined:

$$EcoPI^{i}_{total} = \sum_{m=1}^{8} d_{m_i} + K_{m_i} * N_{m_i}$$

$EcoPI^{i}_{total}$= Eco performance index of intersection i,

m= movement number of the intersection (for standard four-legged intersection m_{max} = 8),

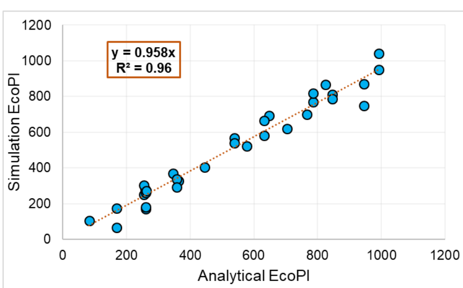
i= intersection number,

d_{m_i}= stopped delay at movement *m* of intersection i (*sec/veh*),

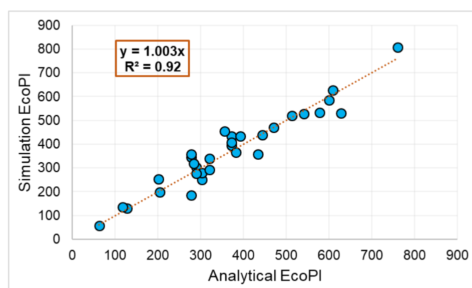
K_{m_i}= stop penalty of movement *m* of intersection i,

N_{m_i}= number of stops at movement *m* of intersection i.

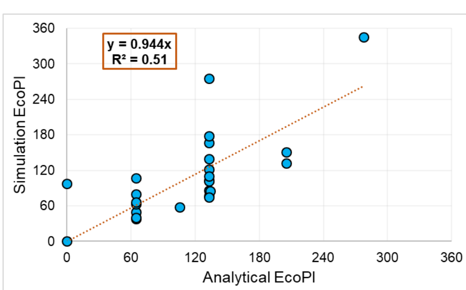
We evaluated Eco-PI estimates (from analytical models) against ground truth from the microsimulation model. Figure I.1.1-2 shows estimated Eco-PIs on a cycle-by-cycle basis from the Market Street intersection on the MLK Smart Corridor for specific protected movements (e.g., through flows) or permitted (or protected/permitted) traffic movements (e.g., left-turn flows). Overall, we find that the Eco-PIs are acceptable for two reasons: 1. Major movements of the network are those served with exclusive phases (e.g., through coordinated movements) and for those movements, the Eco-PIs estimates are reliable; 2. Amount of traffic for protected/permitted phases contributes much less (in the overall intersection Eco-PI) than those of the protected (see for example the magnitude of Eco-PIs by observing y-axis for various movements in Figure II.1.1.2).



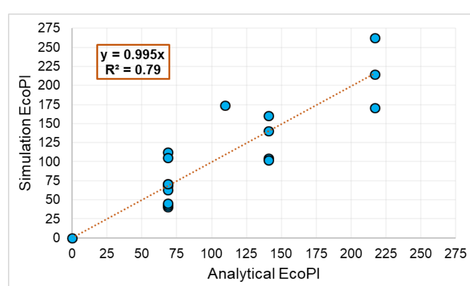
(1) Main street exclusive phases



(2) Side street exclusive phases



(3) Main street in protected/permitted phases



(4) Side street protected/permitted phases

Figure II.1.1.2 Comparison between analytically derived and ground truth Eco-PI.

High-accuracy traffic state prediction models at intersections based on offline/historical data

Improving FC and emissions at intersections requires knowledge of how much traffic is predicted to be arriving at those intersections, hence optimize signal control parameters to accommodate that traffic and fulfill the objective function. The proposed Eco-ATCS relies on predicted turning movements at intersections which allows for signal timings and phasing splits to be optimized in a proactive manner. We used real-time data from cameras to understand travel patterns at intersections and predict the turning movements (through, left and right turns) using graph neural networks (GNNs). To account for the temporal dimension and correlation, we used a 1-D convolution neural network on the graph. Multiple directional features including turning volumes, occupancy, arrivals on green, arrivals on red, green time, red time are among the features that were used in this model. To identify the optimal lookback window and prediction horizon, we performed a sensitivity analysis. Multiple performance measures were used including mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean percentage absolute error (MAPE). The proposed model, Multi Graph Convolutional Neural Network (MGCNN), applies GNN to all signalized intersections along MLK to predict all turning movements. The model was compared to and proved its superiority to several baseline models as shown in Table II.1.1.1.

Developing Constraints for Local/Global Optimization

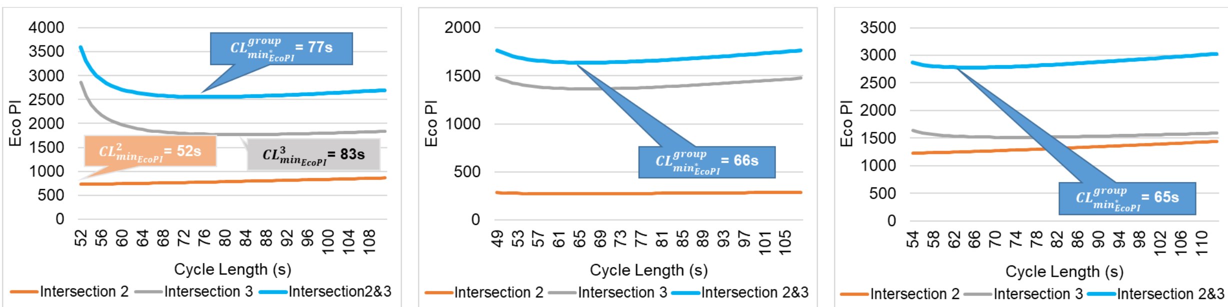
Analytical formulation of Eco-PI is used to develop constraints for local/global optimization. Such constraints will reduce time during signal timings optimization by reducing the "search-space" of feasible solutions. The Eco-ATCS needs to decide in the future (e.g., one cycle ahead) about values for signal timing parameters that need to be deployed. To make such a decision, Eco-ATCS initially start to look for absolute minimum cycle length (CL_{min}^{i}) per intersection (i) to ensure that queued vehicles will be served. Since each intersection belongs

Table II.1.1.1 Performance Comparison with Baseline Methods

Model	Performance Metric	Prediction Horizon (N)				
		1-min	2-min	3-min	4-min	5-min
DCRNN	MSE	3.898	3.911	3.878	3.867	3.876
	RMSE	1.704	1.71	1.702	1.693	1.692
	MAE	0.889	0.888	0.879	0.872	0.865
	MAPE	5.817%	5.897%	5.855%	5.929%	6.007%
T-GCN	MSE	3.076	3.075	3.071	3.074	3.072
	RMSE	1.469	1.469	1.468	1.470	1.470
	MAE	0.778	0.789	0.780	0.790	0.782
	MAPE	4.074%	3.987%	3.994%	3.933%	3.982%
Traditional GCN+GRU	MSE	3.019	3.017	3.018	3.017	3.018
	RMSE	1.457	1.448	1.448	1.447	1.448
	MAE	0.759	0.753	0.754	0.759	0.761
	MAPE	3.993%	3.963%	3.955%	3.919%	3.915%
Traditional GCN+RNN	MSE	1.506	1.513	1.536	1.554	1.559
	RMSE	1.071	1.075	1.081	1.089	1.091
	MAE	0.577	0.602	0.592	0.591	0.608
	MAPE	4.423%	4.33%	4.217%	4.463%	4.334%
MGCNN	**MSE**	**1.452**	**1.489**	**1.494**	**1.504**	**1.504**
	RMSE	**1.051**	**1.065**	**1.067**	**1.069**	**1.069**
	MAE	**0.572**	**0.575**	**0.579**	**0.575**	**0.58**
	MAPE	**4.163%**	**4.223%**	**4.154%**	**4.246%**	**4.205%**

to a group that will work in a coordinated manner where common cycle is required, the system selects a maximum of all identified minimum cycle lengths to represent the minimum group cycle length (CL_{min}^{group}). Further, the Eco-ATCSs evaluate the range of cycle lengths on each intersection in the network by estimating Eco-PI. The minimum cycle length for a group of intersections ($CL_{min^*_{EcoPI}}^{group}$) is a tradeoff between minimum Eco-PI-based cycle lengths of each intersection ($CL_{min_{EcoPI}}^{i}$).

To illustrate, Figure I.1.1-3 depicts the impact of the range of cycle lengths on Eco-PI at one non-critical (Broad street on the MLK Smart Corridor) and one critical intersection (Market Street on the corridor), labeled as intersections 2 and 3. Intersection 2 is non-critical, its volumes are relatively low and thus the optimum conditions (on a local level) might exist for values of cycle length lower than CL_{min}^{group}. However, Intersection 3, which represents a critical intersection, has a CL_{min}^{i}, which is, in most cycles, selected as a CL_{min}^{group}. Thus, any increase in CL_{min}^{group} will improve Eco-PI at intersection 3, up to a certain point (see gray lines). Therefore, by increasing cycle length, intersection 2 usually does not benefit in terms of Eco-PI (observe orange lines). Such trend can be explained by the fact that higher cycle lengths tend to increase delay, which is one component of the Eco-PI. Finally, when Eco-PIs of both intersections are added together, one can observe that the resulting $CL_{min^*_{EcoPI}}^{group}$ is a compromise solution between best-performing cycle lengths from both intersections $CL_{min_{EcoPI}}^{2}$ and $CL_{min_{EcoPI}}^{3}$ (see part *a)*). In this way, $CL_{min^*_{EcoPI}}^{group}$ and belonging green times are determined as an input (constraints) for other optimization procedures.



a) Cycle 1 *b) Cycle 11* *c) Cycle 12*

Figure II.1.1.3 Impact of non-critical and critical intersection CLs on minimum group CLs

Local Signal Control Optimization

Our team focused on two different approaches for signal control optimization locally: game theory (GT) and reinforcement learning (RL).

GT-Approach for Local Signal Control Optimization

In the GT approach, we modeled the intersection signal control problem as a cooperative simultaneous closed form n-player game among the phases of the intersection. Each phase is represented as a player, and the goal of the game is to minimize the Eco-PI. The strategy set of each player is a set of allowable green durations from minimum green to the cycle length. Each player(phase) seeks to choose a green duration that will minimize its own stopped delays through the Nash Bargaining Model. Using Nash Axioms, a unique solution which is a set of optimal green durations is found that minimizes the overall Eco-PI of the intersection.

a. This controller analytically measures delay, stops, and stop penalty, and outputs optimal green time to minimize fuel consumption.

b. $\pi_i(g)$ is the payoff function (Eco-PI) associated with selecting any g from the feasible set of green timings and is defined as:

$$\pi_i(g) = EcoPI(g)$$

$$EcoPI(g) = \frac{0.38 * CL * PF_i * [1 - (\frac{g_i}{CL})]^2}{[1 - (\frac{g}{C}) * \frac{q_i}{s_i}]} + \frac{(FC_D + FC_A)}{FC_I} \cdot b(CL - g_i) \cdot \frac{s_i * (CL - g_i)}{CL * (s - q_i)}$$

g_i = green time of phase I and g_{imin} = minimum green timing of phase i

S = Saturation flow qi = traffic flow of phase PF = Progression Factor

Using a real-world dataset, several simulations were run in a VISSIM simulation model of four intersections along MLK BLVD. Fuel Consumption, Stop Delay, Stops, and Emissions were measured to evaluate the ECO-PI of the game-theoretic controller vs. the actuated control currently implemented along the corridor. Table I.1.1.2 shows the computed Eco-PI for each intersection in the simulation. There was a reduction of 34% in the ECO-PI results of the Nash Bargaining Controller compared to the Actuated Controllers.

Table II.1.1.2 : ECO-PI Computations for All Intersections

	Actuated	Nash Bargain
Interstate 1	4984.86	4330.42
Interstate	5609.78	5025.58
Interstate	6530.33	6331.33
Interstate	9349.21	1666.82
Average	**6618.55**	**4338.54**

RL-Approach for Local Signal Control Optimization

The RL approach uses Q-learning, a model-free RL algorithm, for the optimization based on the following predefined constraints: 1) Cycle length; 2) Fixed phase sequence; 3) Minimum and maximum green signal durations for each phase. The deep Q network is designed with two hidden fully connected layers.

State: we consider two features for each lanes including the number of vehicles and the number of waiting vehicles (i.e., queue length).

Action: there are 20 actions corresponding additional durations for the cycle length from [0-19]. The next cycle length is *CL* (i.e., the constraint of the minimum cycle length) plus the action given by DRL model. After getting the next cycle length, green phases for movements are allocated by number of arrivals recorded in the last cycle.

Reward: Eco-PI: reward = (-1)*EcoPI and Normalized EcoPI: reward = (-1)*EcoPI/cycle_length

Baselines methods: (1) MinCL: the next cycle length is MinCL, (2) MinCL + 10: the next cycle length is MinCL + 10, (3) Fixed Time, (4) RL: Deep Q learning with the reward as EcoPI, and (5) RL with normalized reward: Deep Q learning with the normalized reward.

We conduct experiments at an intersection of Martin Luther King Boulevard and Magnolia Street. The results shown in Figure II.1.1.4 compares the RL-based optimization with other four method mentioned above. There is an average of 27% improvement in Eco-PI during pick hours.

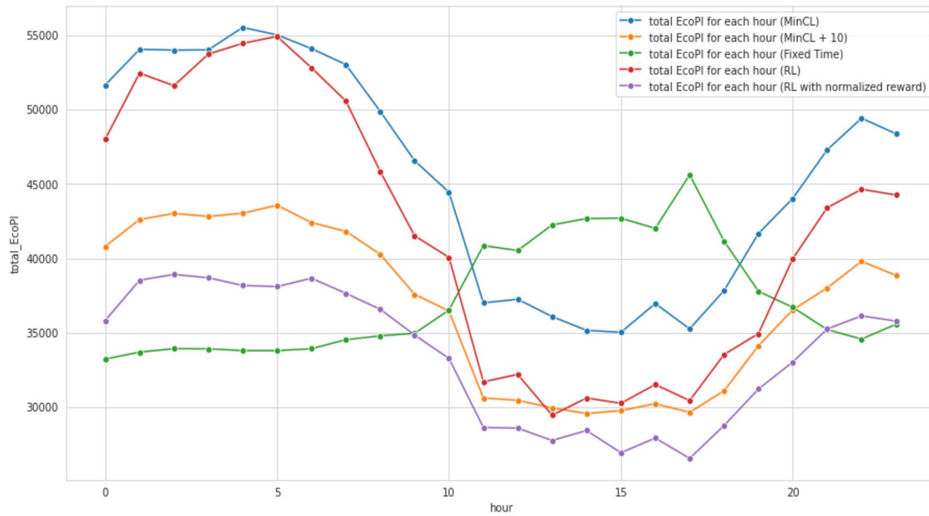


Figure II.1.1.4 Eco-PI computations for one intersection

Conclusions

During the first year of this project, we developed a reliable, low-latency, schema-agnostic, and highly available data infrastructure to provide data from the urban testbed in Chattanooga, TN to all components of Eco-ATCS. A new performance measure was developed to characterize impact of signal timing on excessive fuel consumption and vehicular emissions. Research and development on machine-learning and game-theory based optimization approaches have started. The optimization approach has several modules: traffic state prediction, local control optimization constraints, local optimization, and global optimization. While this is an ongoing project, the current results have shown over 25% improvement in Eco-PI when RL or GT-based local optimization algorithms are applied at intersections. Adding global optimization to the Eco-ATCS during the next budget period, we expect the improvement to increase.

Key Publications

1. Palit, J. and O. A. Osman (2021). A Multi-Graph Convolutional Neural Network Model for Short-Term Prediction of Turning Movements at Signalized Intersections. Will be presented at the 101st Annual Meeting of the Transportation Research Board.

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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. Dalei Wu (email: dalei-wu@utc.edu), UTC for developing RL-based local optimization.

Dr. Yu Liang (email: Yu-Liang@utc.edu), UTC for working on global optimization.

Adian Cook (email: cookas@ornl.gov), ORNL for working on simulation and modeling.

II.1.2 Energy Optimization of Light and Heavy-Duty Vehicle Cohorts of Mixed Connectivity, Automation and Propulsion System Capabilities via Meshed Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) and Expanded Data (Michigan Technological University)

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Start Date: October 1, 2020 End Date: December 31, 2022
Project Funding: $2,587,739 DOE share: $1,999,951 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 Michigan Technological University (MTU) and partnered with AVL Powertrain Engineering Inc. (AVL), Borg Warner (BW), Traffic Technology Services (TTS), American Center for Mobility (ACM) and Navistar (NAV). The project team brings a wealth of prior research and development experience from industry and federally funded projects relating to selfish connected and automated vehicle (CAV), vehicle dynamics and powertrain (VD&PT) energy optimization and connected infrastructure to vehicle (I2V) technologies. The main thrust for the team are to develop a micro-traffic simulation environment with specific VD&PT system attributes and CAV capabilities, 2) field a vehicle test fleet of mixed classification, propulsion and CAV capacity, 3) develop artificial intelligence (AI) and machine learning (ML) based multi-agent optimization methods for various traffic infrastructures, 4) integrate the virtual environment and the optimization methods then deploy the system as a CAV hardware in the loop (HiL) for the vehicle test fleet and 5) conduct closed track and public road testing to validate simulation and demonstrated energy and mobility improvements at multiple scales. Energy reductions at the cohort level are proposed in the range of 10 to 50%, [2],[3], depending on infrastructure scenario and composition of vehicle cohort and CAV technologies and are compared with baseline scenario of identical infrastructure and cohorts without the aid of connectivity and driving automation.

Objectives

The objective of the project is 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. The primary outcome of the cohort optimization output is speed profiles and lane utilization, where appropriate, for individual connected vehicles of the cohort. The optimization of the propulsion system for energy given the cohort optimizer speed profile for individual vehicles with the cohort is handled onboard with previously developed methods. Figure II.1.2.1 summarizes the team's objectives, to simulate and/or test on four traffic infrastructures with various configurations of simulation or test parameters regarding the vehicles, cohort composition, infrastructure details and driving scenario. Overall, the objective is to realize energy consumption reductions at the vehicle cohort level on the driving ranges specified in Figure II.1.2.1, which are upwards of 50%. The team will utilize the virtual environment to define probability distribution functions of energy savings by broadly sweeping parameters of the scenario, utilizing the results to identify specific scenarios to test and demonstrate with the connected and automated vehicle test fleet on closed test track or on public roads that have connected infrastructure via TTS cellular based services.

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.1.2.1 Project energy consumption reduction objectives summarized by traffic infrastructure, showing distances considered and scenario parameterization.

Approach

To achieve the project objectives, parallel activities are in play that 1) develop a comprehensive micro-traffic simulation environment populated with diverse VD&PT models that have V2x connectivity capacity, multi-agent optimization methods focused on cohort energy minimization without compromise to drive safety or drive quality, 2) create a cellular communication based connected vehicle and infrastructure system (CV2x), 3) integrate the micro-traffic simulation + optimization environment into a cloud based, real time CAV HiL bench that is linked to the CV2x network, 4) take existing CAV's from prior and current DOE and ARPA-E projects adding additional hardware and software for a CV2x fleet with real-time cloud based optimization capability and 5) deploy the vehicle test fleet on closed test track and public roads for technology demonstration and simulation environment validation. Figure II.1.2.2 summarizes the overall approach for the project. Note only ACM's facility is depicted in Figure II.1.2.2, but numerous public road infrastructures in southeast Michigan with TTS connected signalized intersections are being utilized for testing and demonstration for the project that are namely multi-lane arterial roadways with fixed and actuation timing signalized intersections.

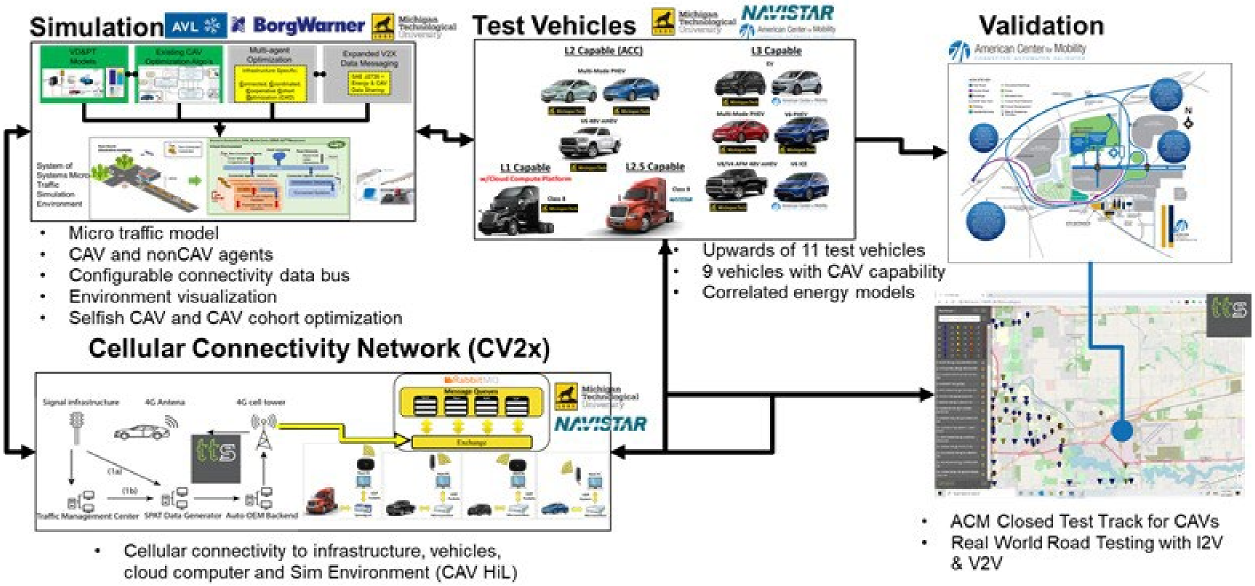

Figure II.1.2.2 Summary of combined math to track to road approach for CAV cloud based HiL cohort optimization for energy reduction demonstration.

The optimal coordination of the vehicle cohorts is a layered approach as depicted in Figure II.1.2.3, showing the loop of connected data exchange from vehicles and infrastructure to the cloud optimizer (optimization methods will be specific to infrastructure) and then back to vehicle. Note, the optimization methods do not provide optimal input for the infrastructure in this project. The optimizers main outputs are vehicle velocity trajectories, lane utilization and cohort vehicle order. The latter two are dependent on the scenario. It is then the task of the onboard controllers to further optimize the powertrain control for additional energy reductions.

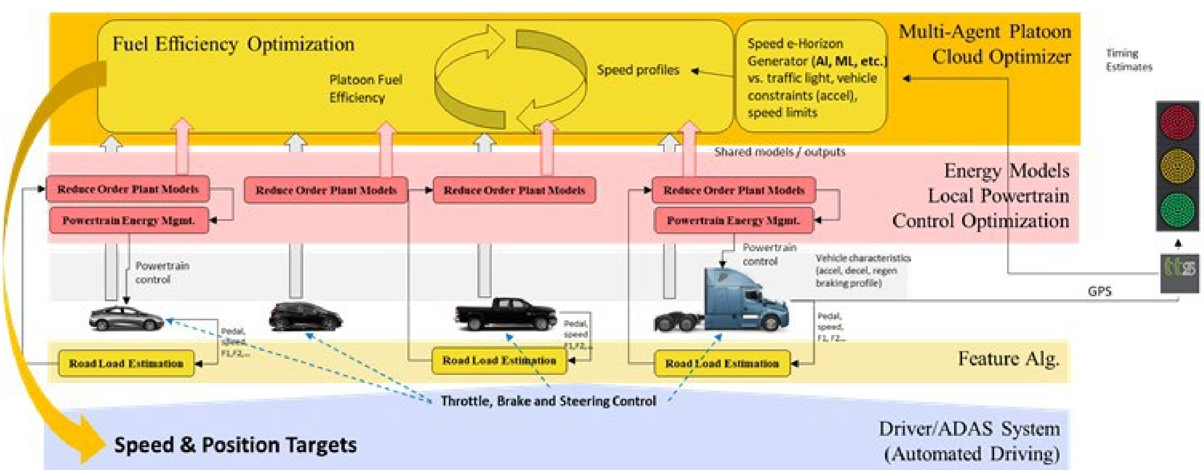

Figure II.1.2.3 Layered approach for cohort coordination using cloud-based optimizer.

The specific details of the optimization methods utilized for this project are best described in Figure II.1.2.4, with trained AI through neuro-evolution techniques coupled with classifier(s) to identify pass/fail criteria, for example the ability of a cohort to successfully negotiate passing a signalized intersection without violating the cohort's integrity. The core of the AI system is shown in Figure II.1.2.5 and has been shown to achieve prediction performance for real-time optimal coordination of the cohort of less than 10 ms, well below the team's goal of 100 ms prediction times. The overall approach is capable of broad range variation of simulation parameters into a design of experiments (DoE) approach that is a significant enable to large batch simulation to develop and report probably distribution functions for potential energy savings that reflect stochastic nature of real-world traffic scenarios and vehicle cohort composition and behavior.

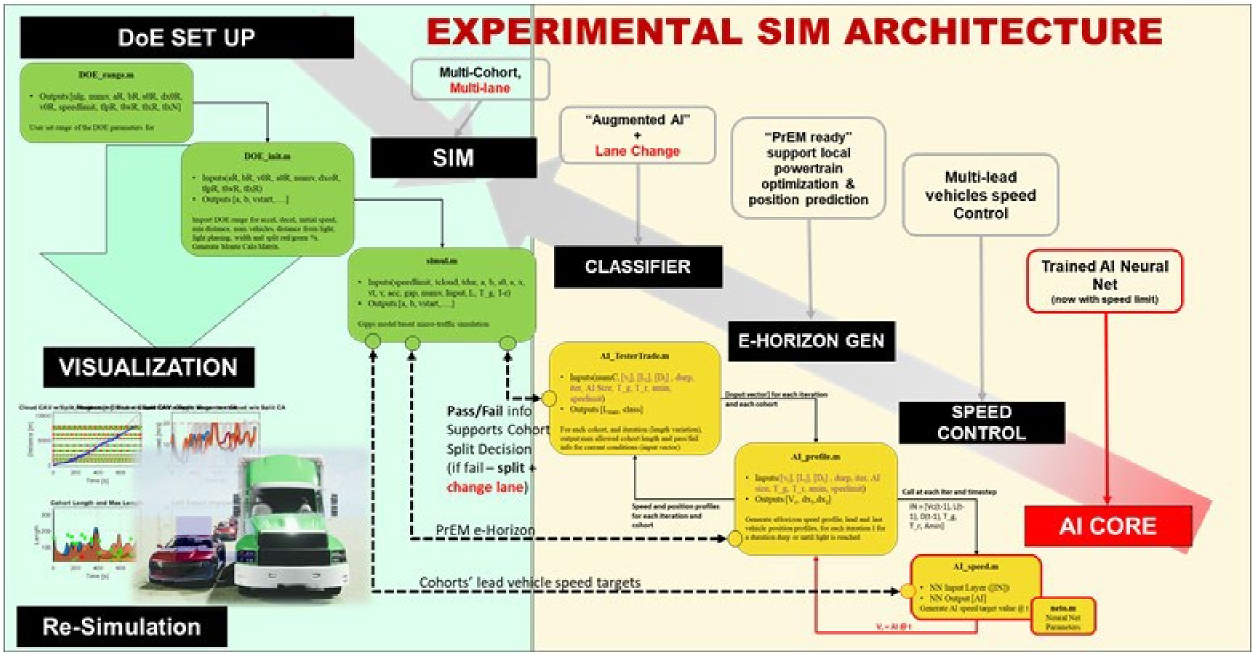

Figure II.1.2.4 Optimization method architecture overview.

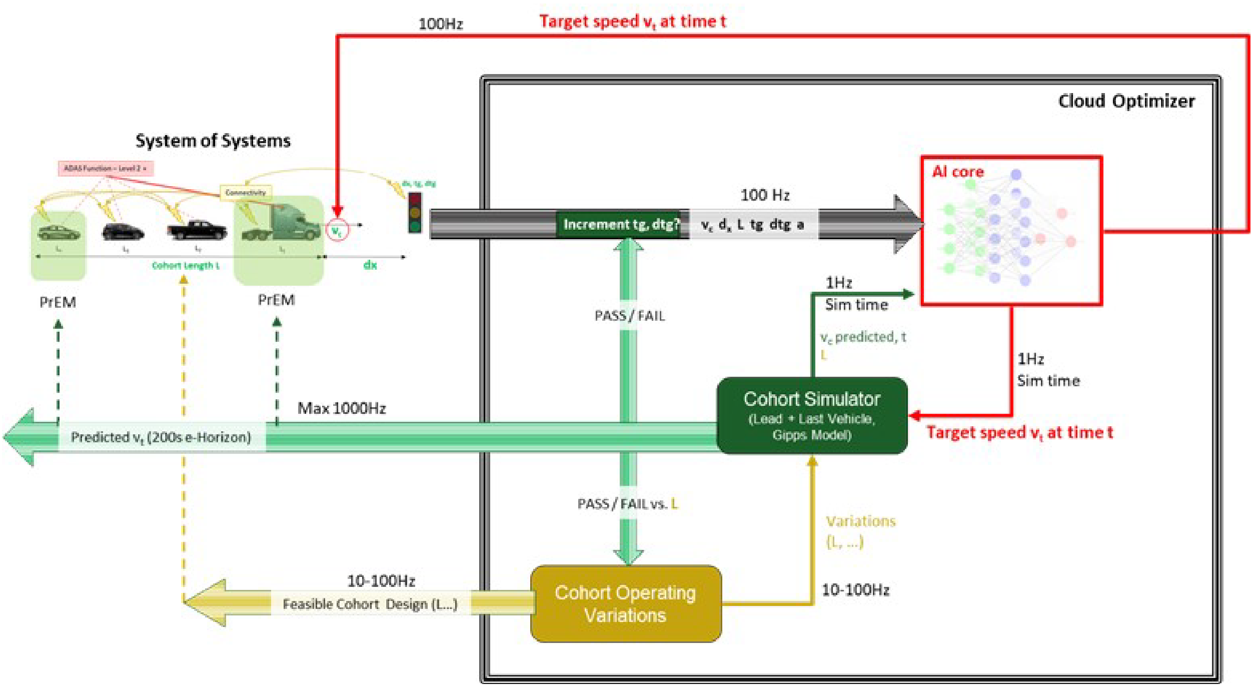

Figure II.1.2.5 Details of the AI + Classifier and signal exchange.

The integration of the simulation environment, optimization and VD&PT models has been done exclusively in MATLAB/Simulink and is coupled with proprietary AVL tools that enable common connectivity and communication amongst models and with varying time steps. Python scripting, data queuing services and

4G/5G cellular communication will make the vehicle demonstration possible in the second phase of the project.

Results

The team has successfully developed the capability to model and optimize cohort behavior for energy optimization on single lane single and multi-signalized intersections as well as multi-lane, multi signalized intersection roadways (arterial roadway). Figure II.1.2.6 shows a single scenario of mixed vehicle cohort operation on a single lane, multi-signalized intersection roadway and the benefits to synergizing connectivity with automated driving. On the left of Figure II.1.2.6, the vehicles are highly automated only with ACC and no connectivity. The middle trace, all vehicles in the cohort are connected to each other and with the AI optimizer that has signalized intersection data. The plot on the right is the connected AI plus the classifier to determine ability to maintain cohort integrity and pass the next signalized intersection. For this scenario it is readily seen the benefits of the optimization process as the cohort's trajectory smoothly navigates the traffic maze without having to stop at a single traffic light. The resulting energy savings is 17% for the cohort with the AI alone and an addition 10% reduction is possible when the AI is combined with the classifier output. Individual VD&PT combinations realize energy savings in kJ's and as percentage at different rates relative to the specific operation and calibration of the powertrain. The largest physical energy savings, in kJ, is for the heavy-duty truck, but on a percentage, basis is a light duty truck with mild hybridization, lower right of Figure II.1.2.6.

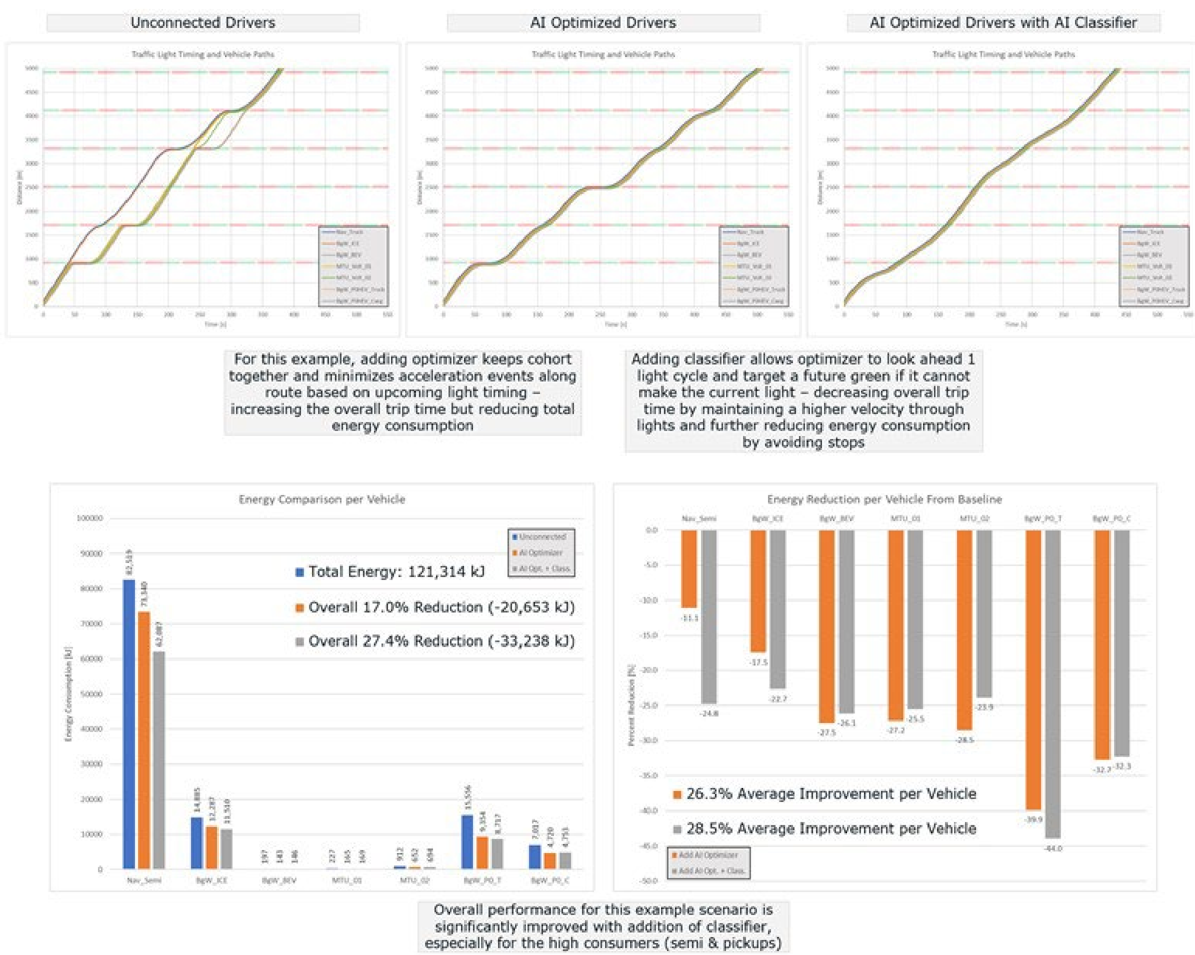

Figure II.1.2.6 Results for seven vehicle mixed cohort operating on a single lane, multi-signalized intersection traffic maze with only automation (left), connectivity + AI optimization (middle) and connectivity + AI optimization + classifier (right).

Results from the simulation environment for a multi-lane arterial roadway in which the vehicle cohort is allowed to split and change lanes to achieve optimal energy and try to minimize transit time were also achieved. Figure II.1.2.7 contains these results from a 15,000 run DoE highlighting the effect that cohort splitting has on energy consumption performance and transit time as function of the number of vehicles in cohort and the number of traffic lights. The benefits to energy and transit time become more pronounced and apparent as the number of vehicles in cohort and number of traffic lights increase.

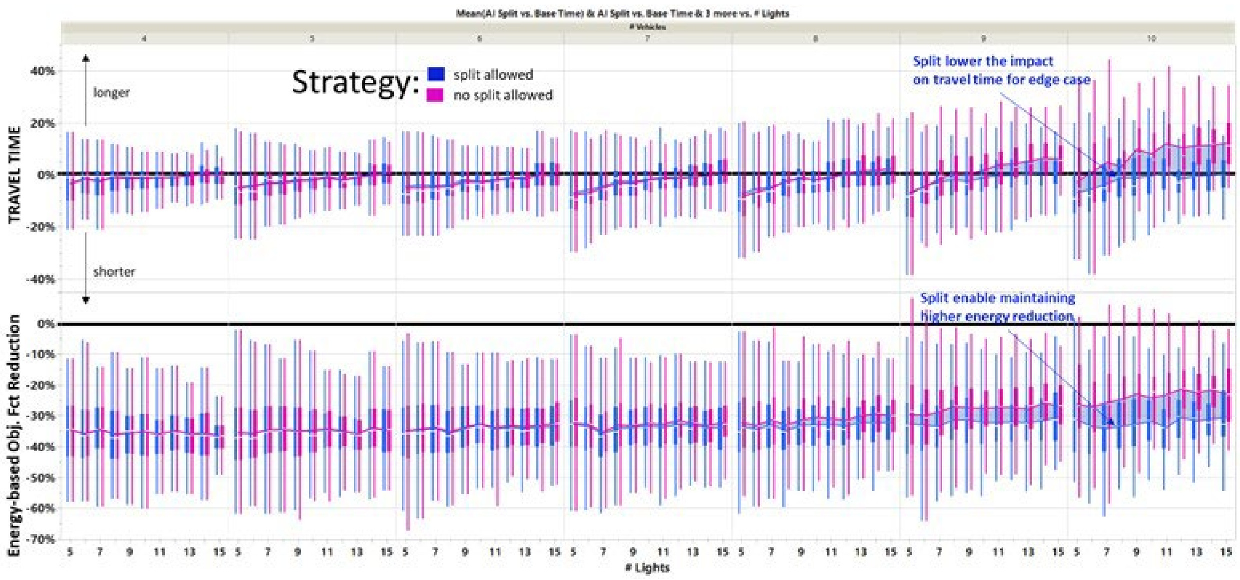

Figure II.1.2.7 Influence of AI optimization to split mixed vehicle cohort to achieve reduced energy consumption and minimal transit time impact on multi-lane arterial roadway as a function of number of vehicles in cohort and number of traffic lights.

Conclusions

As of November 2021, the project team has developed two of three infrastructure optimization methods, single lane signalized intersection(s) and multi-lane arterial roadway and integrated them into the system of systems simulation environment and have demonstrated on a few driving scenarios energy reductions within the objective range identified and at least greater than 10%. The use of AI as the multi-agent optimization method significantly reduced the prediction time below 10 ms, enabling real-time implementation. The introduction of a classifier further improves the energy saving

The next steps for the project are to:

- Complete the third infrastructure optimization method for limited access highway and integration into the simulation environment.
- Perform preliminary demonstration of the optimization technique with a subset of the available connected vehicle test fleet at signalized intersections in November of 2021.
- Continue mechanizing the simulation environment to enable wide range of parameter variation for DoE batch studies to determine distribution of energy saving potential of the optimization methods.
- Continue the maturing the CV2x network that links the simulation environment as a cloud-based CAV HiL and cohort optimization tool.

Key Publications

Submitted, Under Review

1. Jacquelin, F., Bae, J., Chen, B., Knopp, D., Orlando, J., and Robinette, D., “Automated Vehicle Cohort Speed Optimization via Neuroevolution,” IEEE International Conference on Robotics and Automation, Philadelphia, PA, 2022.

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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.

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Acknowledgements

This material is based upon work supported by the U.S. Department of Energy’s Office of Energy Efficiency and Renewable Energy (EERE) award number DE-EE0009209. The project PI would like to acknowledge the combined team of Michigan Technological University (MTU), AVL Powertrain Engineering Inc. (AVL), Borg Warner (BW), Traffic Technology Services (TTS), American Center for Mobility (ACM) and Navistar (NAV) for their close cooperation, resource sharing and collaborative efforts in develop the virtual environment and constituent components, optimization algorithms and the retrofitting and development of a CV2x vehicle test and demonstration fleet. The entire project team would also like to thank DOE for their time and commitment to the project Nicolas D’Amico, Erin Boyd, Danielle Chou, and Daniel Nardozzi.

II.1.3 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 the 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 a significant potential to reduce energy consumption and fuel costs. They also require 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 for large-scale transit electrification by developing effective planning and operation tools and identifying strategies to improve 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

The research team has completed the initial model formulation of an integrated optimization model that considers the potential charging schedules and charging costs in the charging infrastructure planning stage for an isolated BEB line. The proposed model simultaneously optimizes the location and sizing of charging stations, the on-board battery capacity, and the charging schedules for a BEB system, with the objective of minimizing both the upfront costs and the expected charging costs of the bus system. Moreover, the model explicitly considers electricity demand charges and the time-of-use (TOU) rate structure. A numerical experiment using five battery electric buses has been conducted to test the effectiveness of the proposed model.

Smart Operation of Electric Buses

The research team is developing a simulation-based optimization model to optimize the charging scheduling for a fast-charging BEB system, effectively minimizing total charging costs. With on-route fast charging, BEBs are as capable as their diesel counterparts in terms of range and operating time. However, on-route fast charging makes it more challenging to schedule and manage charging events for a BEB system. First, on-route fast charging may lead to high electricity power demand charges. Second, it may increase electricity energy charges because of the charging that occurs during peak hours. Without careful charging scheduling and management, on-route fast charging may significantly increase fuel costs and reduce the economic attractiveness of BEBs. We will simulate the operating patterns of each bus and determine an easy-to-use rule of when to charge BEBs for transit operators. Charging costs include both electricity demand charges and energy charges.

Electric Bus Energy Estimation and Optimization

The energy estimation and optimization task focuses on adapting NREL's Route Energy Prediction (RouteE) software and, more specifically, the module that performs the mesoscopic energy predictions, now known as RouteE-powertrain, to accurately predict energy consumption for diesel and battery electric transit buses for transit system planning and operations optimization.

The approach includes three major activities to achieve the goal of transit bus specific RouteE-powertrain models for optimal energy use in transit system planning and operations. The first is collection of real-world bus drive cycle data that include empirical energy consumption, as reported by the vehicle. The second major activity is development and training of RouteE-powertrain estimators for transit buses. RouteE-powertrain is a statistical model that relies on training data with some "ground truth" energy consumption dimension, which could be empirical or modeled with powertrain simulation software. Empirical, vehicle-reported energy consumption is used in this work. Given the COVID-19-related logistical challenges affecting the collection of on-road bus data from UTA vehicles for this work, resulting in delays in data collection efforts until late in the year, NREL developed preliminary RouteE models using an alternate transit bus data set available through NREL's Fleet DNA commercial vehicle database. The bus data were originally collected in partnership with the Santa Clara Valley Transportation Authority (SCVTA). This data set included 68,482 miles of data for hybrid electric (HEV) and 6,377 miles of data for battery electric (BEV) buses; no conventional diesel buses were included. The GPS trajectories collected from these buses are plotted in the map shown in Figure II.1.3.1.

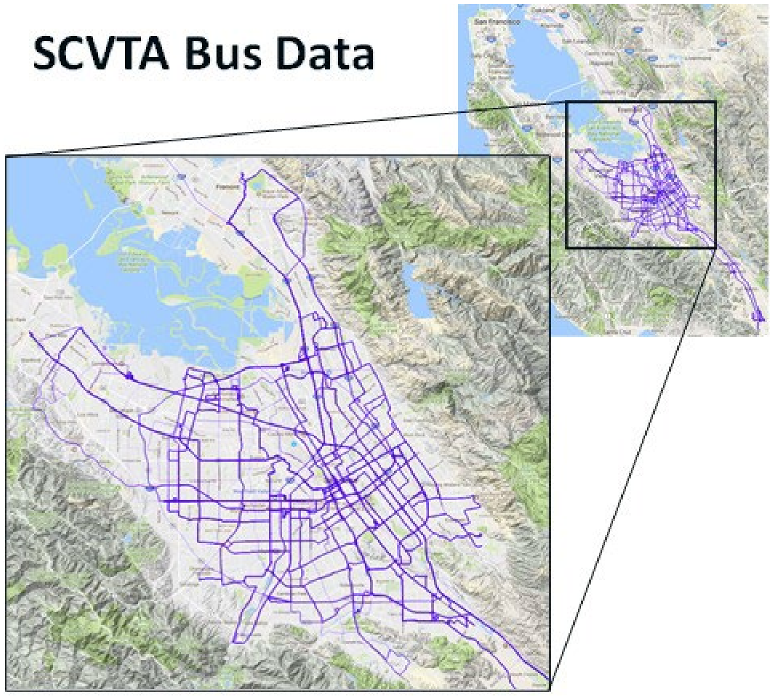


Figure II.1.3.1 GPS trajectories for ~75,000 miles of bus operation data provided by Santa Clara Valley Transportation Authority (SCVTA)

Finally, the third major activity is to add any transit-specific customization into the RouteE-powertrain modeling approach. As RouteE-powertrain was originally architected to accurately predict energy consumption for light-duty passenger vehicles and certain medium- and heavy-duty freight vehicles, researchers at NREL anticipated needing to develop novel approaches to account for significant impacts on energy consumption, such as variable ridership, HVAC loads, and extended idle periods.

Grid Impact Analysis and Evaluation

The project's approach to assessing the impact of electric bus charging will include grid modeling with both measured and simulated data as inputs. By measuring real performance of electric buses on distribution networks and comparing with the performance of various charging strategies and scenarios, it is possible to determine best practices for operating a fleet of battery electric buses on a distribution-constrained power system. In addition, the team will investigate how BEBs can provide bulk grid services to a regional network, including the bus charger's ability to respond to demand response and frequency regulation commands from a balancing authority or other grid operator.

Since the Utah Transit Authority (UTA) started deploying electric buses, it has been monitoring how energy and peak demand charges affect the bills it pays to operate the high-power, on-route chargers and the slower depot chargers. Important to the deployment of BEBs on the large scale is identifying ways to reduce peak charges for individual chargers and for the aggregation of the fleet operator's BEB and non-BEB loads; thus, monitoring and control are particularly important. To assess the impact of the BEB chargers on the grid, a detailed distribution network model is necessary. The team has received models for several distribution networks from Rocky Mountain Power, the utility that owns the networks. The network models serve as the framework to analyze how the electric load created by the BEB chargers impacts the loading of equipment and the range of network voltages across the entire network. Important metrics such as equipment loading, and network voltages can be compared between BEB deployment levels and charging strategies. In addition, the utility has provided some data from the substation to help estimate the non-UTA loads that share the distribution network with the UTA.

Electric Bus User Behavior and Stakeholder Study

To complement the research on the operational and quantitative aspects of transit bus electrification, the researchers have also made efforts to study the perceptions of transit riders and non-riders as well as fleet operators toward BEB adoption. The study adopted two different approaches in this area. To study the perceptions of transit fleet operators, a set of expert interviews was designed and will be administered to transit agencies. To study the perceptions of riders and the public towards BEBs, two stated-preference surveys were designed. These surveys will offer important perspectives and enhance our understanding about possible gaps that exist among the operational capabilities of BEBs, the awareness of BEBs by transit operators, and the public's knowledge of BEBs.

The study on agencies and operators seeks to understand the challenges and perceptions of BEB adoption. This study aims to understand information that will be acquired through individual interview sessions centered around stakeholders' personal insights regarding electric buses and transportation in general. By understanding individual perspectives and insights, a hypothesis as to what prohibits adoption advancement can be formed and tested in future research endeavors. The results are expected to directly contribute to the advancement of electric bus adoption in the industry.

The study uses surveys of both transit users and non-users, entailing similar questions. The user survey employs a survey methodology and a stated-preference choice experiment to quantify users' beliefs. Survey subjects will be sampled from the current ridership of UTA buses, and the survey will be administered onboard the bus lines. Targeted riders will include both individuals who have ridden on a BEB (specifically UTA Line 2) as well as those who have ridden on non-electrified lines. The non-rider survey will be administered online to a representative sample of the Salt Lake City area population.

Results

Integrated Electric Bus Fleet and Infrastructure Planning Model

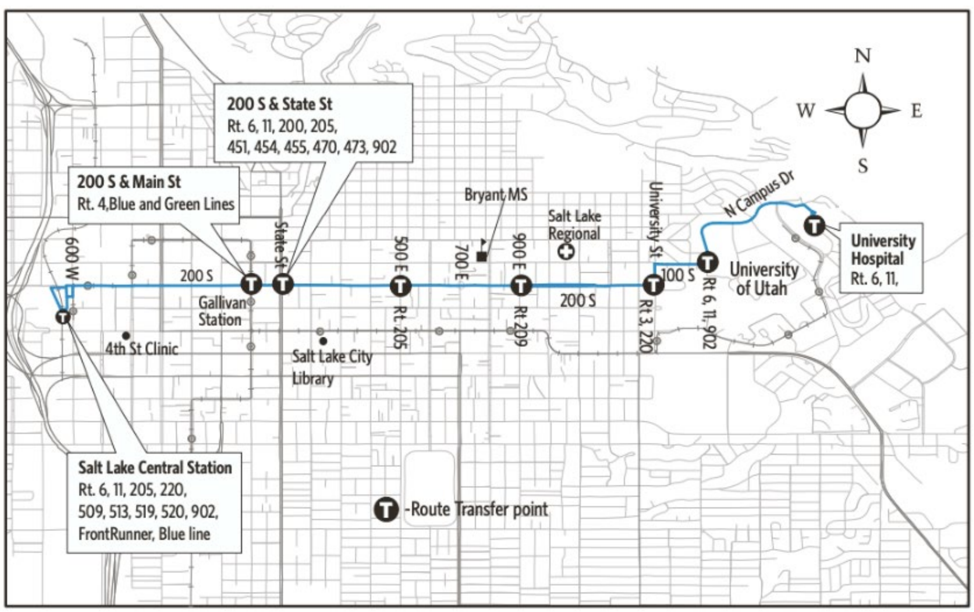


Figure II.1.3.2 Bus network for numerical experiments/UTA

The proposed optimization approach was tested on a UTA bus route (route 2) with five BEBs in Salt Lake City, Utah, as shown in Figure II.1.3.2. Bus route shapefiles are extracted from the Utah Automated Geographic Reference Center. Bus fleet size and timetables are obtained from the Utah Transit Authority website. Average bus ridership is obtained from UTA. Nominal bus driving speed profiles are generated based on the bus timetable and the speed limit on each road segment. We adopt the energy consumption model proposed in [1] to evaluate the energy consumption rate of the buses in this network.

The optimization model is solved using a GAMS [2] and a CPLEX [3] solver on a 3.40 GHz Dell computer with 16 GB of RAM. The optimal solution of the model is reported in Table 1. The optimal vehicle battery size, depot charger power, and on-route fast charger power are 48.9 kWh, 10 kW, and 150 kW, respectively. Figure II.1.3.3 shows the battery SOC profiles of each BEB from the five bus lines. One can observe that the SOC of every BEB throughout a day is within the specified range (i.e., 20% to 90%), which implies that the designed battery size, the charger deployment, and the charging schedule can ensure the normal operation of the BEB system. According to the UTA timetable, route 2 has a round trip length of 10.9 miles. It serves 55 service loops every day, which indicates a daily service mileage of 599.5 miles. Based on the optimized daily charging costs shown in Table II.1.3.1, the optimal energy cost per mile is $0.44 for May to September and $0.37 for October to April.

Table II.1.3.1 Optimal Costs for BEBs on Route 2

Amortized Daliy Costs	May through September	October through April
Total Costs	$326.20	$283.00
Battery Costs	$39.00	$39.00
Charger Costs	$22.80	$22.80
Charging Cost	$264.40	$221.20

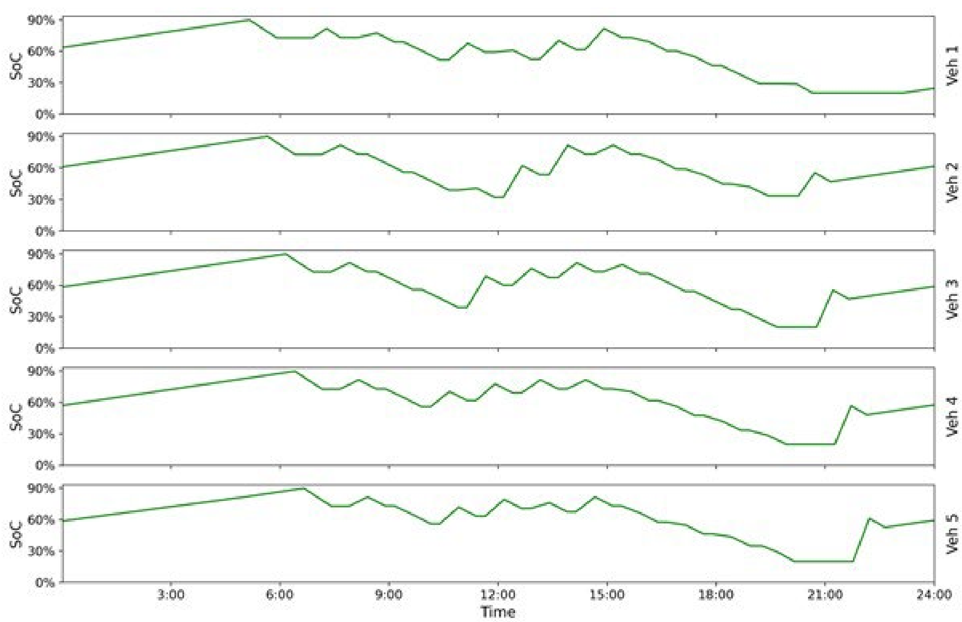
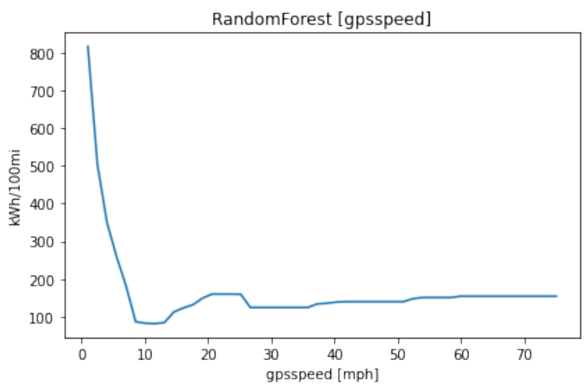


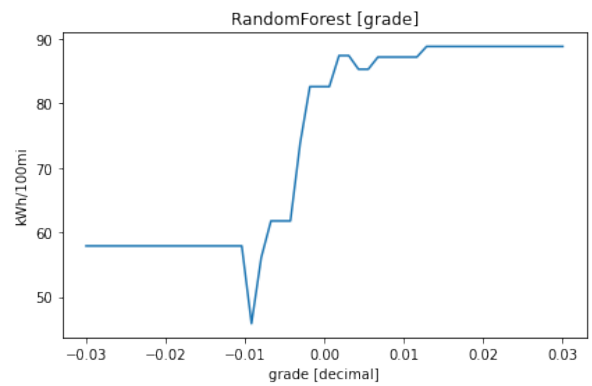
Figure II.1.3.3 Optimal SOC chart for five BEBs on route 2/USU

RouteE-Powertrain Model Development

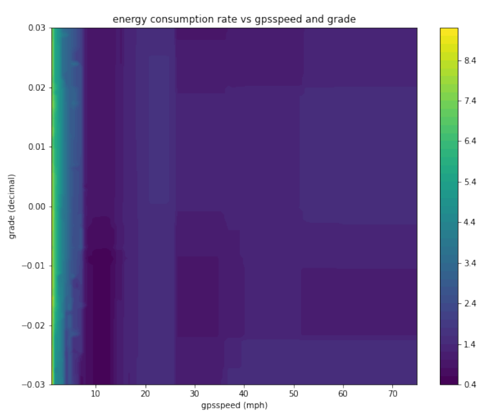
As described in the approach section, RouteE-powertrain models have been successfully trained in FY21 for HEV and BEV buses based on the data provided by SCVTA. Mesoscopic energy prediction, such as RouteE-powertrain, of hybrid powertrains (especially heavy-duty) presents many challenges, including unknown powertrain control strategies and initial battery state-of-charge (SOC). In addition, HEV buses are beyond the scope of this project and will not be included in final project deliverables. For these reasons, the RouteE-powertrain results for HEVs are not included here. However, a RouteE-powertrain model was trained using the BEV data from SCVTA, and those results are shown in Figure II.1.3.4. Model performance was validated on a holdout set of training data, and the model was found to have a trip normalized root mean squared error (NRMSE) of about 11%, which is quite good at this stage in the model development process. It is clear from the results in Figure II.1.3.4 that general energy consumption trends are captured; however, significant uncertainty remains and must be addressed. As previously discussed, transit-specific considerations must be addressed in the RouteE-powertrain approach to more accurately model bus energy consumption. This is evident in the preliminary results shown here. Bus HVAC loads and variable ridership are both likely factors impacting energy consumption in ways that are not currently being considered in RouteE-powertrain.



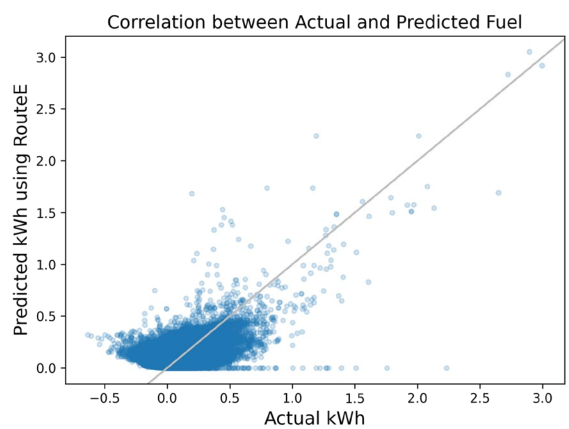
(a) model results for speed vs. energy consumption rate



(b) model results for road grade vs. energy consumption rate



(c) 2D contour showing the model results for both speed and grade vs. energy consumption rate



(d) scatter plot showing predicted vs. actual energy consumption for each road segment

Figure II.1.3.4 RouteE-powertrain results from training on SCVTA BEV data, considering only [speed, grade] as model feature/NREL

Conclusions

The focus of FY 21 was on initial model development. Preliminary results of the integrated electric bus fleet and infrastructure planning model demonstrated that the proposed model can effectively reduce energy costs per mile, lower up-front battery and charging infrastructure costs, and bring down bus charging costs. In addition, this project is one of the first to demonstrate training of RouteE-powertrain on “ground truth” vehicle-reported energy consumption data instead of simulated energy consumption. Preliminary results from training on a very limited set of BEV data from SCVTA show promising results—namely, 11% NRMSE—even for a simple model that only considers speed and road grade as prediction features. Model performance is expected to improve significantly when the larger on-road data set from UTA is used for model training.

Furthermore, transit bus specific customizations, such as consideration for HVAC loads, variable ridership, and extended idle periods, will also increase model accuracy.

Key Publications

1. Yiming Zhang, Yi He, Zhaocai Liu, and Ziqi Song, "Integrated Optimization of Timetable and Charging Scheduling for a Battery Electric Bus System." Presentation at the Transportation Research Board (TRB) 101st Annual Meeting, Washington, D.C., January 9–13, 2022.

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1. Yan Wang, Jianmin Jiang, Tingting Mu, "Context-aware and energy-driven route optimization for fully electric vehicles via crowdsourcing," *IEEE Transactions on Intelligent Transportation Systems* 14, no. 3 (2013):1331–1345.

2. IBM ILOG, CPLEX V12. 1: User's Manual for CPLEX. International Business Machines Corporation, 2009.

3. Richard E. Rosenthal, GAMS−A User's Guide. GAMS Development Corporation, Washington, D.C., 2012.

Acknowledgements

This research is supported by the Department of Energy Vehicle Technologies Office, under the Energy Efficient Mobility Systems (EEMS) Program. The authors would like to thank the Utah Transit Authority (UTA), Tri-County Metropolitan Transportation District of Oregon (TriMet), and Rocky Mountain Power (RMP) for their continuous support in data sharing and field implementation.

II.1.4 Energy-Efficient Maneuvering of Connected and Automated Vehicles (CAVs) with Situational Awareness at Intersections

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Start Date: October 1, 2019 End Date: December 31, 2022
Project Funding: $4,214,135 DOE share: $3,207,135 Non-DOE share: $1,007,000

Project Introduction

The increased development of Connected and Automated Vehicle (CAV) systems, currently used for safety and driver convenience, presents new opportunities to improve the energy efficiency of vehicles. Southwest Research Institute (SwRI) concluded a project that demonstrated 20% reduction in energy consumption on a Toyota Prius Prime 2017 plug-in hybrid by leveraging information streams enabled via connectivity—Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I) and Vehicle-to-Everything (V2X). The effort was part of the Next Generation Energy Technologies for Connected and Automated on-Road Vehicles (NEXTCAR) program funded by the Advanced Research Project Agency-Energy [1]. The energy consumption gains were achieved by a combination of vehicle dynamics and powertrain control algorithms with a focus on SAE L1 and L2 automated vehicles where a human is still responsible for safe operation. The increased traction gained by the Mobility-as-a-Service (MaaS) movement is stimulating investment in the development of L4 and L5 automated vehicles. A life cycle assessment by the University of Michigan [2] indicates that subsystems in such highly automated vehicles could increase vehicle primary energy use and GHG emissions by 3−20% due to increases in power consumption, weight, drag, and data transmission. The application of NEXTCAR style technologies on such highly automated vehicles could not only improve their energy consumption but also provide additional opportunities for energy savings given the improved sensing and actuation capabilities of such vehicles. Also of interest is how infrastructure-based mobility solutions can be applied from an efficiency perspective.

From a technical standpoint, this program addresses three fundamental questions:

1. While technologies like eco-driving in CAVs have shown great potential for energy savings, how do these savings translate with respect to different types of powertrains—Internal Combustion Engine Vehicles (ICEV), Hybrid Electric Vehicles (HEV), Plug-In Hybrid Electric Vehicles (PHEV) and pure Electric Vehicles (EV) as well as different levels of automation—L0 through L4 vehicles?

2. Existing studies show that significant improvement in energy consumption is possible even with limited levels of automation such as cruise control [3],[4]. Programs like NEXTCAR integrate V2V and V2I connectivity with simple automation mechanisms and proved that benefits up to 20% is feasible. While such improvements were achieved at an individual vehicle level, what is the effect of these 'smart' vehicles at a system level under realistic traffic scenarios?

3. Can infrastructure mobility solutions such as intelligent intersection platform contribute to more than safety applications and help in achieving system-level energy benefits?

Objectives

The primary objective of this project is to develop and demonstrate CAV technologies and scenarios that enable ≥ 15% reduction in energy consumption at a system level without negatively impacting traffic flux as shown in Figure II.1.4.1.

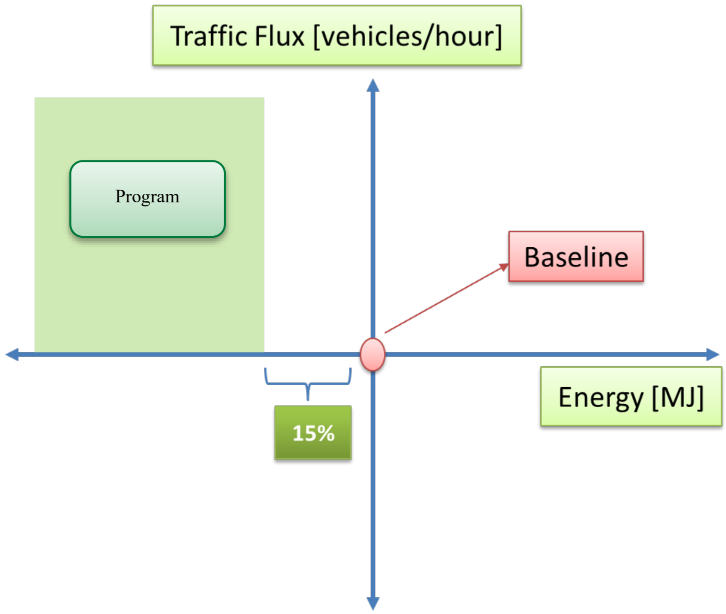

Figure II.1.4.1 Program Objective

Approach

To better understand the impact of CAV based energy saving technologies on different vehicle platforms, a mix of vehicle as shown in Figure II.1.4.2 was chosen. These six vehicles form the 'ego' vehicle set and are selected based on powertrain type and automation levels. V2X connectivity is a common theme across the ego vehicles.

		Automation Levels				
		L0	L1	L2	L2+	L4
Powertrain	ICE	Hyundai Elantra				Chrysler 300
	HEV					
	PHEV			Toyota Prius Prime		
	EV			Kia Soul	Tesla Model 3	Easy Mile EZ 10

Colour	Contribution
Orange	Hyundai contribution
Green	Continental contribution
Light blue	SwRI contribution

Figure II.1.4.2 Ego Vehicle Set

The ego vehicle set needs to be tested under realistic traffic scenarios. Generating repeatable traffic scenarios for on-road testing is challenging and at times, not feasible. Some traffic patterns are dangerous and weather patterns add to noise factors. It is unclear whether calibrations and control strategies are producing the desired effect or whether environmental factors are influencing results. Therefore, the team built a traffic simulator as part of this effort. An urban corridor in Columbus, Ohio as shown in Figure II.1.4.3 was modeled and calibrated for realistic traffic flow patterns in the PTV Vissim environment.

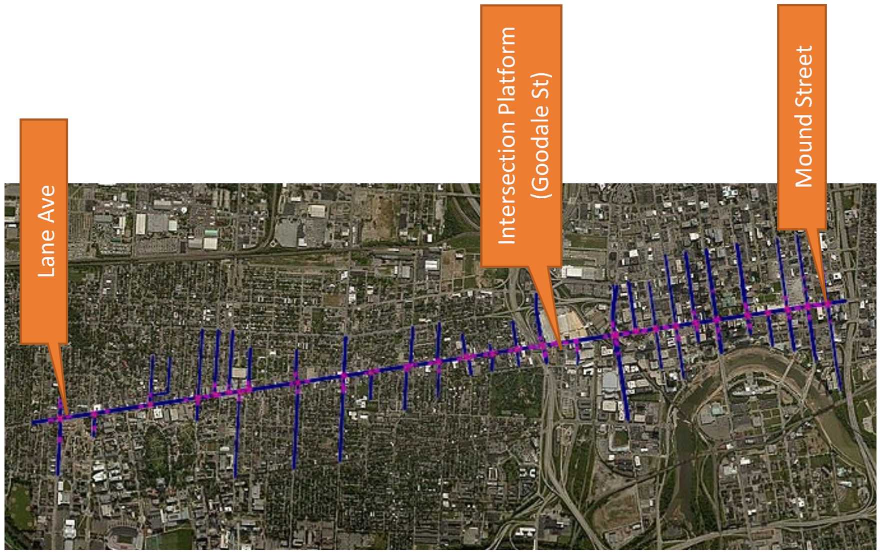

Figure II.1.4.3 Urban Corridor in Columbus, Ohio (High Street)

The intelligent intersection platform concept built by Continental, one of the project team members, is shown in Figure II.1.4.4. The intersection platform uses conventional automotive sensors such as radars, cameras along with a Dedicated Short-Range Communication (DSRC) radio. The system can accommodate other sensors such as LIDAR as well. The intersection platform leverages these sensors in conjunction with an environment model to develop a comprehensive scene understanding akin to a 'virtual' traffic police. In addition to scene understanding, the system is also able to create 'proxy' Basic Safety Messages (BSMs) and Personal Safety Messages (PSMs) on behalf of non-connected entities. This information can be sent to connected vehicles via the DSRC road-side unit mounted on the stack. While the intersection stack was primarily designed for safety applications and augmenting sensor information for L4 vehicles, the ego vehicle set in this program will receive the messages from the intersection platform and optimize their approach. Energy savings enabled via the intersection stack is quantified.

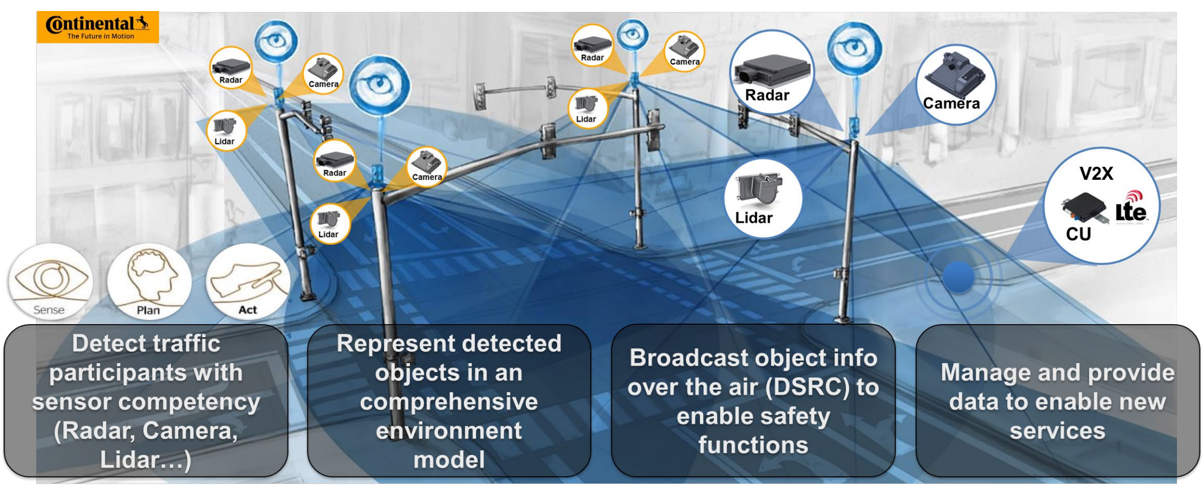

Figure II.1.4.4 Intelligent Intersection Concept

Figure II.1.4.5 describes the overall technology that is being built as part of this program and how the above-mentioned technologies blend together. L0-L3 vehicles use an advisory system to guide a human driver while L4 vehicles can directly integrate the information into their trajectory planning module and optimize their approach. Frost & Sullivan, the Tech-to-Market (T2M) partner for the program, brings market forecast studies that was used to tune three key parameters for the study - (1) Vehicle powertrain mix (2) V2V and V2I penetration and (3) Vehicle Automation. Energy consumption impact at a system level was studied under different scenarios by tuning these parameters.

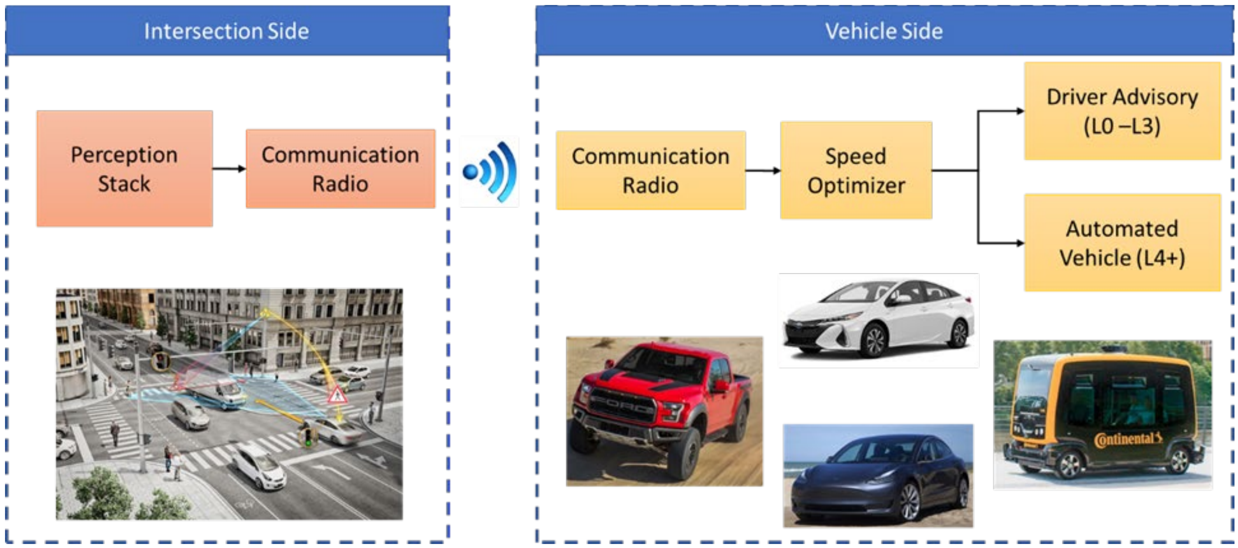

Figure II.1.4.5 Technology Approach

The focus of this reporting period (10/01/2019 – 12/31/2021) was on software-in-the-loop validation of the technology and transitioning to vehicle testing on chassis dynamometer. The software framework involving both traffic simulation and vehicle powertrain simulation were validated based on real-world observations. The team completed the software-in-the-loop testing via full factorial experiment designs to identify the impact of four key factors on corridor level energy consumption: (1) Traffic Flux (2) Powertrain electrification (3) Vehicle-to-vehicle penetration and (4) Smart vehicle penetration. Various conditions were identified that enable achievement of the program performance target of 15% corridor-level energy consumption reduction. The team devised a framework for down selection of scenarios to run on a vehicle chassis dynamometer. A summary of milestones along with their corresponding status is shown Table II.1.4.1. Vehicle testing is in progress and initial results are consistent with results from large scale simulation studies.

Table II.1.4.1 Milestone Summary (As of Q8)

Milestone	Description	Type	Due	Completion Status
Intersection stack validated with real traffic data	Validate operation of the intersection stack with real traffic data.	Technical	Q9	100%
Demonstrate 15% energy savings via proposed methodology in simulation	Final demonstration of energy consumption benefits in simulation for overall fleet.	Technical	Q9	100%
First draft of Techno-Economic-Analysis complete	Generate a cost performance model that provides insight into the trade-offs and interactions between product design, cost, and performance.	T2M	Q9	100%
Demonstrate 10% energy savings on a Connected Automated Vehicle (CAV) dynamometer	Demonstration of energy consumption benefits on a hub dynamometer integrated with a real-time traffic simulator.	GO/NO-GO	Q9	80%

Vehicle Simulation

The team completed a comprehensive simulation study under various scenarios and quantified improvements at a corridor level. The simulation sweep consisted of a full factorial of the following parameters:

1. Eco-driving and connected ('smart') vehicle penetration:
    A. Control: No Smart vehicles
    B. Low: ~25% of vehicles traversing through the whole corridor are smart
    C. Medium: ~50% of vehicles traversing through the whole corridor are smart
    D. High: ~75% of vehicles traversing through the whole corridor are smart
2. V2V Penetration:
    A. Full V2V and V2I penetration in the corridor
    B. Zero V2V penetration. Smart vehicles utilize only radar and V2I→ operate with information about the approaching traffic light state and one lead vehicle for eco-driving
3. Traffic Conditions:
    A. 0.25x maximum volume supported by the corridor (low traffic)
    B. 0.50x maximum volume supported by the corridor (moderate traffic)
    C. 0.75x maximum volume supported by the corridor (heavy traffic)
    D. 1.00x maximum volume supported by the corridor (very heavy traffic)
4. Vehicle powertrain type:
    A. Kia Soul EV – Electric Vehicle
    B. Tesla Model 3 – Electric Vehicle
    C. Toyota Prius Prime – Hybrid-Electric Vehicle
    D. Hyundai Elantra – Internal Combustion Engine Vehicle
    E. Chrysler 300 – Internal Combustion Engine Vehicle

Vehicle Testing

The team approached this milestone in three steps:

1. Establish statistical significance of benefits from large scale simulation study.
2. Down-select speed traces from the simulation studies that adequately represents the variation in the population for all five vehicles.
3. Vehicle testing to confirm benefits agree well with predictions.

Steps one and two are complete and the team is currently conducting vehicle testing. From approximately 45,000 speed traces run in simulation, about 80 traces per vehicle were chosen to be tested on the dynamometer. The traces were carefully chosen to capture variations with respect to trip energy and time for both eco-driving and baseline vehicles.

Tech to Market (T2M)

On the T2M side, the team focused on public sector engagement and Techno-Economic Analysis (TEA). Discussions were held with multiple public sector entities to understand challenges towards real world deployment of the technology. The TEA involved four models that build upon each other to culminate in an overall picture of cost-benefit for various stakeholders—vehicles owners and cities that take part in the deployment and operation of the technology. These models are organized as four modules addressing:

1. Equipment adoption
2. Energy efficiency gained from adoption
3. Other consequences such as emissions
4. Financial impact.

Results

Intersection Stack Validation

Infrastructure to vehicle (I2V) functionality was evaluated by Continental using real-world data from a pilot intersection deployed in Auburn Hills, Michigan. Data comprised of recordings from the intersection and a differential GPS (DGPS) equipped connected vehicle taken over various times of day and traffic conditions in January 2021. Position, heading, and speed of DGPS equipped vehicle are compared to the position, heading and speed sensed by the infrastructure under all possible conventional maneuvers (left, through, or right) on all possible approaches.

Figure II.1.4.6 and Figure II.1.4.7 captures the accuracy and performance summary results of the IIS platform.

	Accuracy Requirement				
Target ->	<1.5 m	< 3m	< 0.75 m	< 5 [deg]	< 7.5%
Maneuvers	Avg Position error [m]	AVG Longitudinal error [m]	AVG Lateral error [m]	AVG Heading Error [deg]	AVG Speed Error %
2 straight	0.75	0.45	0.47	1.97	6.50
6 straight	0.92	0.92	1.08	2.43	7.95
4 Right	0.85	0.39	0.73	3.80	11.54
6 Right	1.21	0.70	0.29	4.31	24.17
8 Right					
2 Right	0.70	0.40	0.73	3.02	13.03
3 Left	0.85	0.39	0.73	3.80	11.54
1 Left	1.38	1.29	0.50	1.24	7.16
7 Left					
5 left	1.59	0.68	1.30	2.71	29.64
Average	1.03	0.65	0.73	2.91	13.94
	PASS	PASS	PASS	PASS	FAIL

Figure II.1.4.6 Intersection Platform Performance

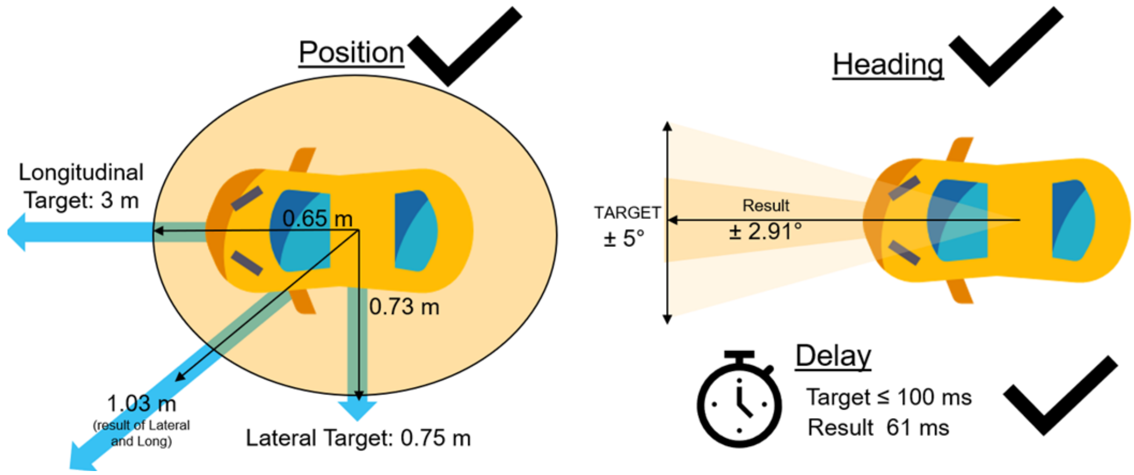

Figure II.1.4.7 Technology Approach

With the current Environmental Model (EM), high discrepancies between the IIS and actual vehicle speed occurred when the test vehicle decelerated for stopping and accelerated again after stop. When speeds below 4 m/s were filtered out in evaluation, the test case passed with an average error of 6.71%. The team is currently working on EM improvements to improve speed error.

Additional System Tests

- Differentiation between Vehicle and Vulnerable Road User (VRU) classification passed, correctly classifying 99.53% of 1208 vehicles and 100% of VRUs.
- Pedestrian position in the form of personal safety message (PSM) accuracy was not evaluated due to unreliable GPS reference system. PSM will be re-evaluated.
- Pedestrian group detection not tested due to COVID pandemic.
- BSM/PSM/SPAT/MAP message mandatory fields passed system requirements. A dummy SPAT payload was used for this testing due to outdated software version on Siemens Traffic Light Controller.
- Delay between RDI (cluster) information receive and BSM transmission passed requirements with an average delay of 104 ms.
- BSMs from connected vehicles were filtered from broadcasted BSM list and passed the test case.
- Per the requirement BSMs and PSMs must be broadcast every 100 ms. Transmission rate tests passed with an average transmission rate of 60 ms for BSMs and 61 ms for PSMs.

Traffic Simulation

Traffic volumes and other parameters for the selected corridor in Columbus, Ohio, were updated in the traffic simulation environment to match within 10% of real-world observations during the last budget period. Traffic volumes in the base corridor were significantly low resulting in negligible vehicle-to-vehicle interactions. Therefore, additional calibrations were created to test the eco-driving algorithm and its effects on other vehicles at larger traffic volumes. Additional calibrations were created to test the eco-driving algorithm and its effects on other vehicles at larger traffic volumes. Each link was calibrated for the largest number of vehicles that it could accommodate. Traffic volumes were maximized to a point where intersections did not completely clear traffic queues and began creating backups. The “chokepoint” in the model, i.e., the link with the smallest capacity, can accommodate a volume of 800 vehicles per hour. This was chosen as the upper limit to the number of baseline or eco-driving vehicles that can be introduced into the simulation, since any more would not be able to travel through the chokepoint. In the “Max” capacity scenario, each link contains roughly the maximum number of vehicles that it can handle. A section of this calibration is shown in Figure II.1.4.8, where the southernmost link accommodates about 1,000 vehicles per hour, while the northernmost link can handle over 1,800 vehicles per hour. In each link, 800 vehicles per hour are baseline or eco-driving vehicles that travel the entire corridor, and the remainder is composed of baseline vehicles that enter and travel only a certain segment(s) and exit. Traffic scenarios containing 75%, 50%, and 25% of this maximum number of vehicles (0.75xMax, 0.50xMax, 0.25xMax) were then developed. Original signal timing patterns were preserved.

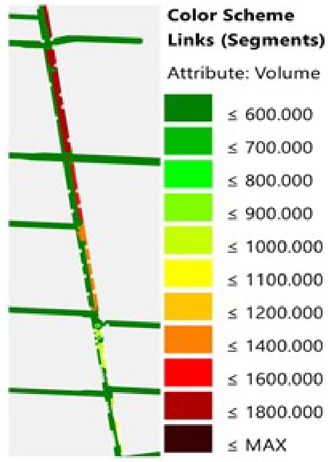

Figure II.1.4.8 Maximum volumes for portion of high street corridor

Quantifying Technology Penetration Value

A visualization of the vehicle composition in terms of baseline vehicles (that travel fully through the corridor) and partial baseline vehicles (that exit or enter through intermediate side roads) over the corridor is shown in Figure II.1.4.9. This plot takes a snapshot of the entire corridor at a simulation time of 1,800 seconds and partitions the entire corridor into 30 bins, each 200 meters in length. The size of each bubble corresponds to the total number of vehicles in each bin, while the color displays the composition of those vehicles between “partial” and “full” baseline. For example, the bottom bubble means that there are approximately 30 vehicles in the first 200 meters of the corridor, with roughly 80% of those composed of “full” baseline vehicles. The next 200 meters has fewer vehicles, and a smaller penetration of baseline vehicles. Figure II.1.4.10 shows how this composition changes over time and location. This captures the challenge of representing technology penetration in urban corridors with multiple entry and exit points by using a single number—for example, 10% penetration of smart vehicles.

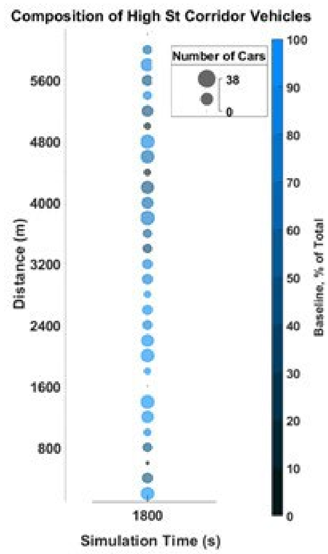

Figure II.1.4.9 Composition of vehicles at a given time

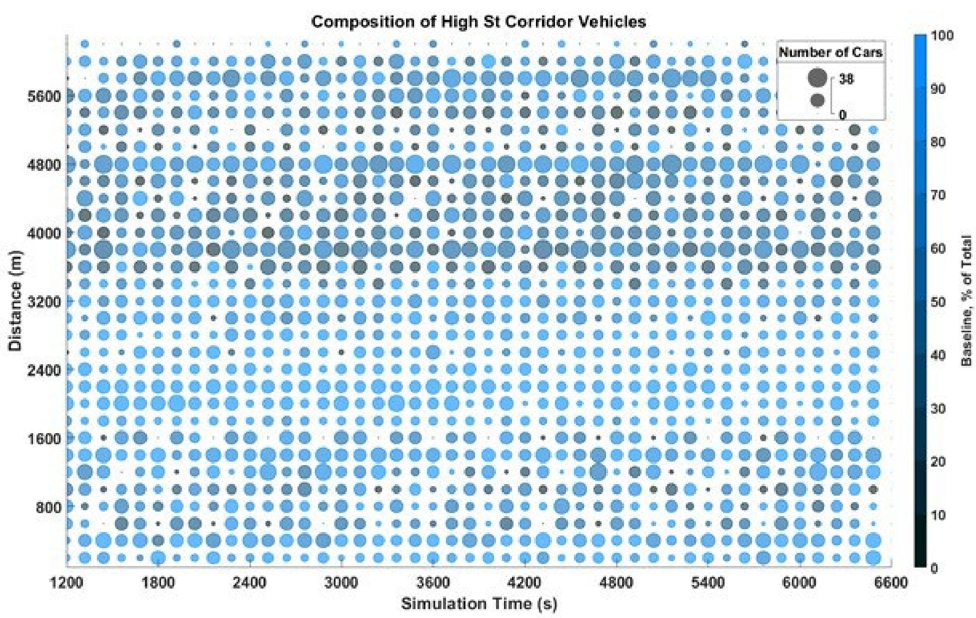

Figure II.1.4.10 Composition of vehicles in High Street corridor

For this study, we define the penetration of smart vehicles based on the proportion of vehicles that travel fully through the corridor. We also note that many vehicles that enter and exit through intermediate side roads might or might not be influenced by these smart vehicles.

Vehicle Simulation

In total, approximately 92,000 powertrain simulations were performed to capture the energy consumption benefits for any given scenario. These numbers are depicted in Figure II.1.4.11. A subplot with the title "SoulEV" consists of the energy consumption reduction under various scenarios assuming all the vehicles on the corridor were of this type. The "2025 New Vehicle Sales Mix" subplot is made using a weighted mean of the five powertrains (Soul EV, Model 3, Prius, Elantra and Chrysler 300). These weights are reflective of new vehicle sales in 2025 as predicted by Frost & Sullivan. The distribution roughly translates to 9.5% EVs, 59% ICEs and 31.5% HEVs + PHEVs. We assume that the number of EVs is split equally between the two EV models (Kia Soul EV and Tesla Model 3). ICE vehicles (Hyundai Elantra and Chrysler 300) are handled in a similar way.

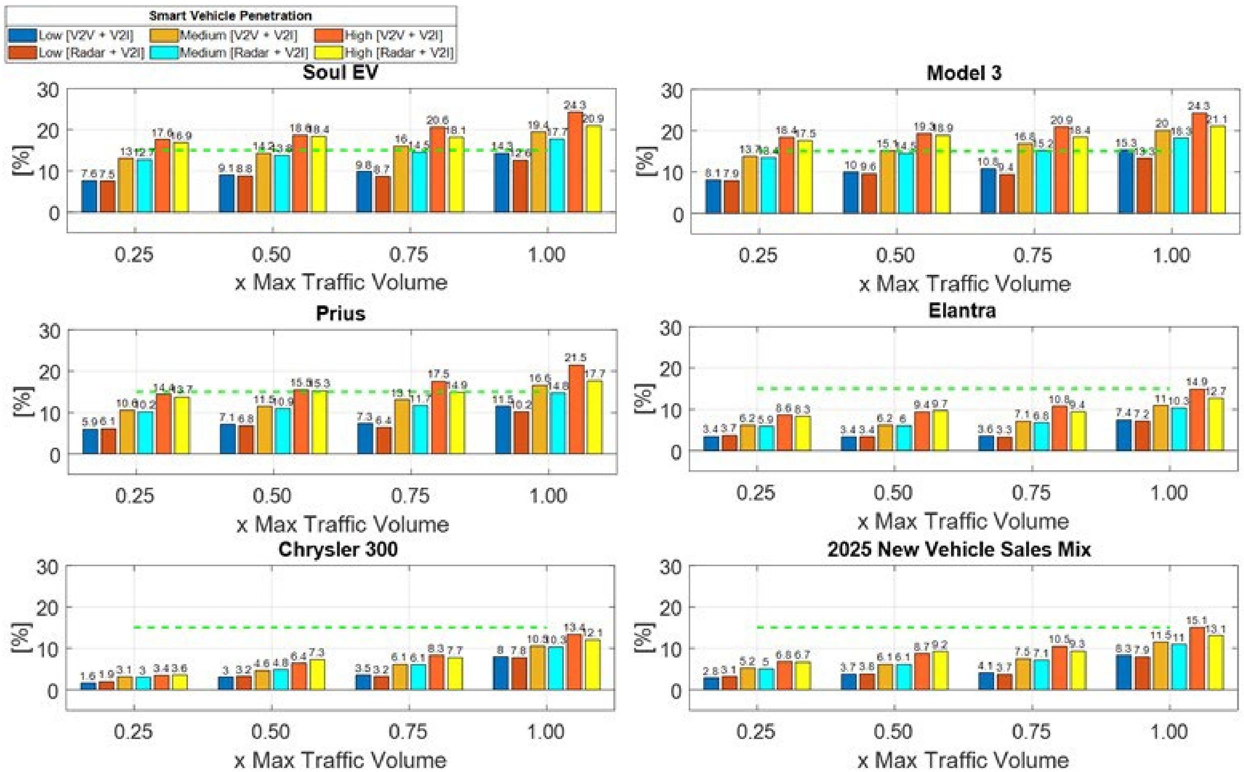

Figure II.1.4.11 Corridor level energy consumption benefit summary (simulation)

The following conclusions can be drawn from the simulation studies summarized in Figure II.1.4.11

1. Electrified powertrains benefit significantly from eco-driving technologies. Even at low penetrations of smart vehicles, a corridor constructed exclusively of Kia Soul EV or Tesla Model 3 meets the energy consumption target at high traffic volumes where there are sufficient vehicle-to-vehicle interactions. At moderate penetration of smart vehicles, this is achieved even at lower traffic volumes.

2. The ICE exclusive corridors approach 15% improvement only in very heavy traffic and higher smart vehicles penetration cases. The nonlinearity of an ICE fuel consumption map will pose challenges to solutions at the corridor level. For example, controlling the corridor at a certain speed might be optimal to a Hyundai Elantra but sub-optimal to a Chrysler 300 or a Ford F-150.

3. Hybrid vehicles such as the Toyota Prius Prime fall between the pure EV and pure ICE vehicles as expected in terms of benefit trends.

4. The corridor based on 2025 new vehicle sales mix (60% ICE, 30% hybrid and 10% pure electric vehicles) crosses the energy savings threshold in very heavy traffic with high penetration of smart vehicles. As future sales mix is expected to trend towards powertrain electrification, we can expect corridor level energy consumption benefits to improve with CAV technologies like eco-driving.

5. In majority of cases, energy consumption benefit from a (Radar + V2I) package is within 2% of benefits from a (Radar + V2V + V2I) package.

Shown in Figure I.1.1.12 are sample two-dimensional scatterplots of energy consumption and trip time of the C300 separated by the 16 combinations of traffic volume 'xMAX' and eco penetration 'Eco.' The subplot heading (with beige and green background) indicates the corresponding combination of 'xMAX' and 'Eco.' The speed traces of the default driver are marked in blue while those of the eco-driver are marked in magenta.

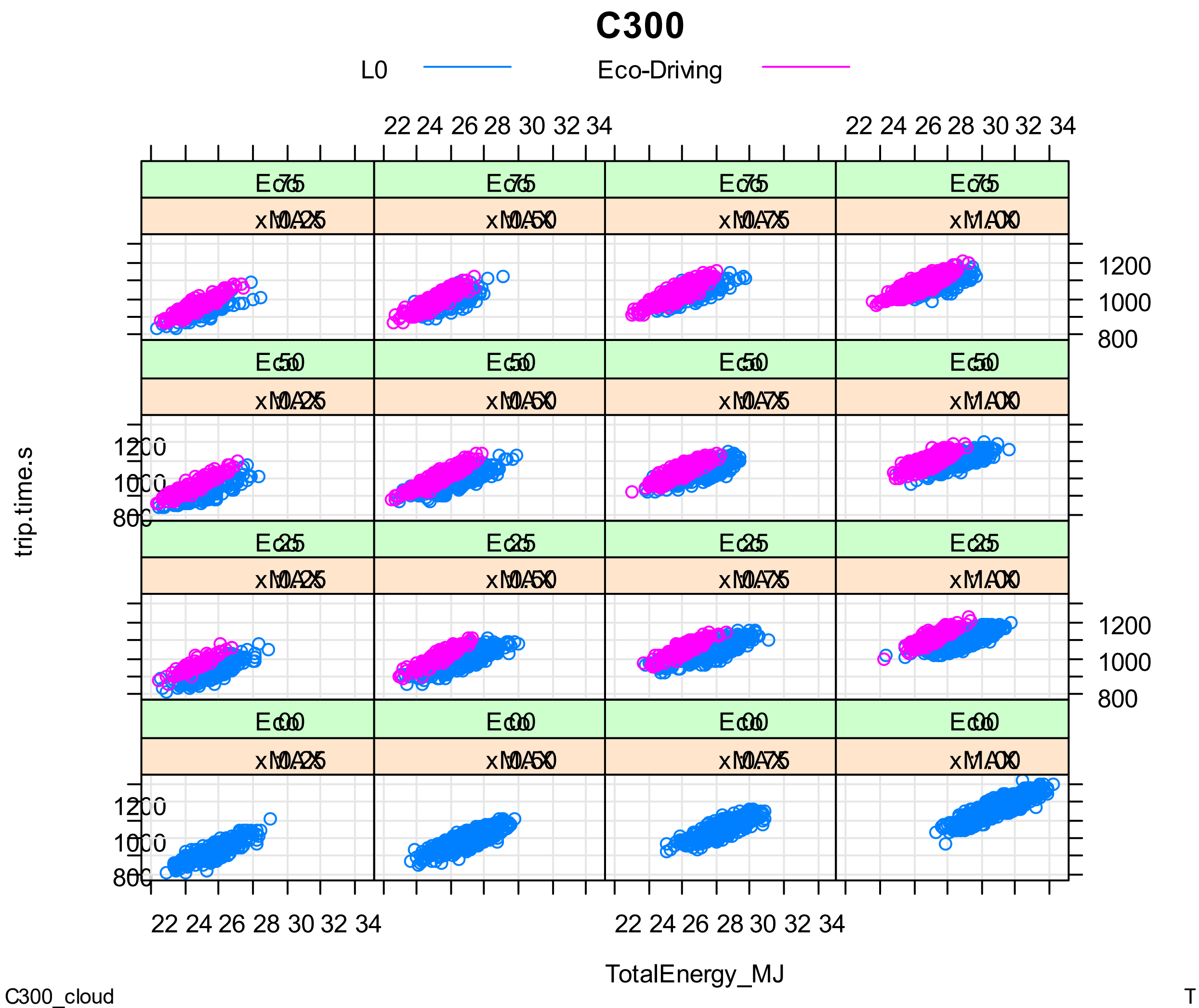

Figure II.1.4.12 Two-dimensional representation of simulation runs; this chart includes 9194 runs of C300; each run is a point

- The four levels of traffic volume 'xMAX' are labeled '0.25' (light), '0.50' (moderate), '0.75' (heavy), and '1.00' (very heavy). As one moves left to right across the subplots, the traffic volume increases from 'light' to 'very heavy' at the given level of eco penetration.

- The four levels of eco-penetration 'Eco' are labeled '00' (no eco-drivers, baseline driver only), '25' (low penetration), '50' (medium penetration), and '75' (high penetration). As one moves bottom to top across the subplots, the eco penetration increases from nil to 'high.'

Within any subplot, it is important to acknowledge the variance in energy consumption and trip time of the blue and magenta trips even when the factors we control (xMAX and Eco) are fixed. The variation is a result of noise factors that we do not control. These include the time at which a vehicle (default or eco-driver) enters the simulation, the phase and timing of the many signals relative to the entry time, the number of partial-trip vehicles etc. The partial-trip vehicles travel only a portion of the corridor and are not included in the energy calculation—but they do impact the energy consumption of the vehicles of interest i.e., those completing the full trip from the chosen origin to the chosen destination.

Establishing statistical significance of energy consumption benefits

Figure II.1.4.13 is laid out similarly to Figure II.1.4.12 except that the default driver in the baseline corridor (bottom row of Figure II.1.4.1) is incorporated into the other subplots. The three distributions of energy consumption are labeled ‘base.L0’ in blue (default driver in control corridor), ‘EEMS.L0’ in magenta (default driver in EEMS corridor), and ‘EEMS.Eco’ in green (eco driver in EEMS corridor). Notice in Figure II.1.4.12 that the magenta (eco driving) and the blue (default driving) clouds overlap but the magenta clouds are shifted left relative to the blue clouds. Visually, it appears that eco-driving consumes less energy with trip times comparable to the default driving

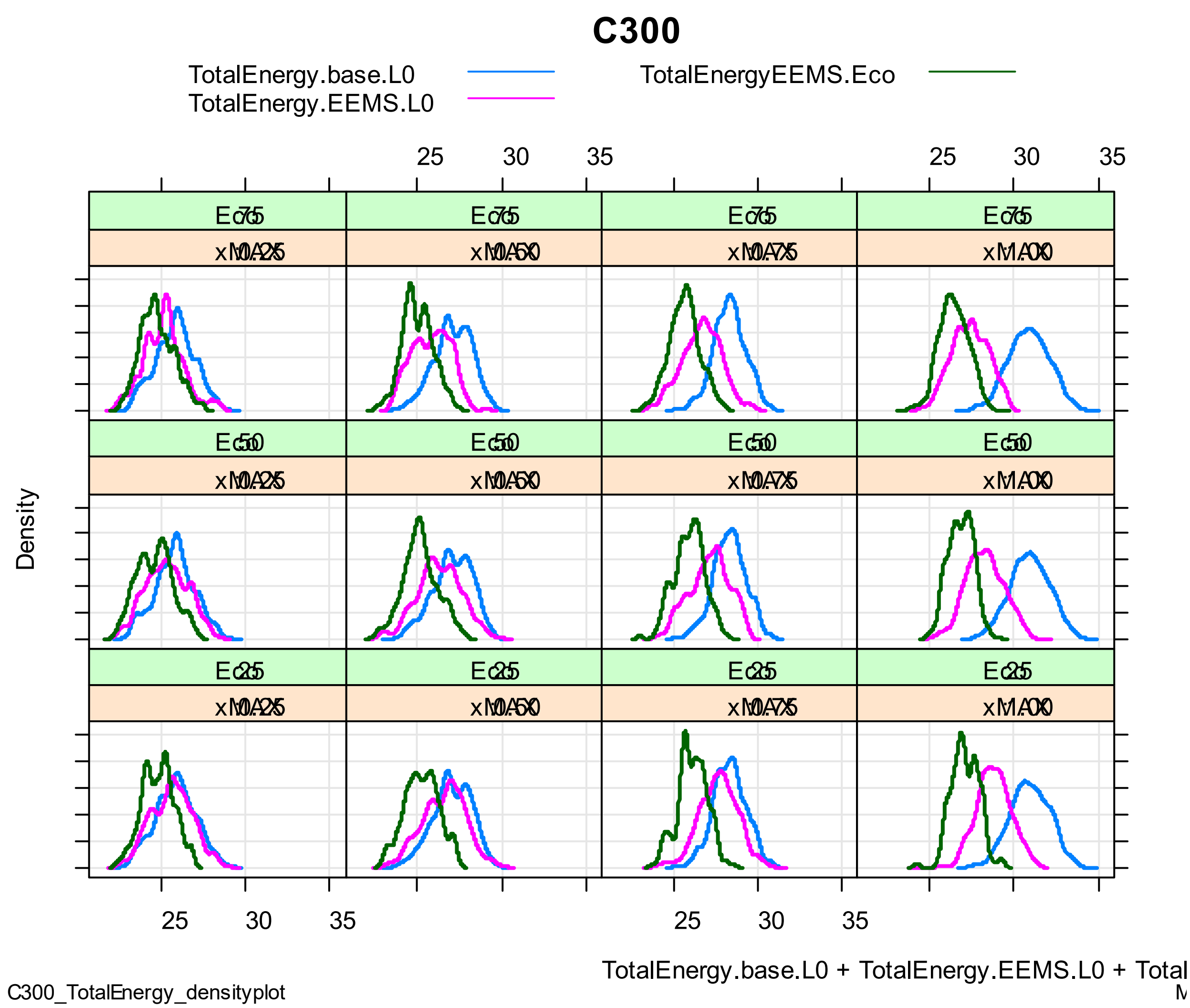

Figure II.1.4.13 Marginal distribution of energy consumption of C300 for the default driver in control corridor (blue), default driver in EEMS corridor (magenta), and eco-driver in EEMS corridor (green)

Since some of the distributions show characteristics that not representative of a conventional normal distribution (ex: two humps), a non-parametric study was conducted to capture the difference in energy consumption means along with corresponding confidence intervals. This Monte Carlo based boot-strapping approach is described in simple terms below:

1. Select a level of xMAX; that is, a column of subplots in Figure II.1.4.14. Say we select xMAX=1.00 – the rightmost column.
2. Select a level of Eco within the column. Say we select Eco=75 – the top right panel.
3. Let N denote the total number of points (speed traces) in the selected panel. These points are 'stratified'; i.e., they are either 'L0' (blue) or 'Eco' (magenta). Let N1 and N2 denote the number of blue and magenta points respectively.
4. We randomly draw, with replacement, N1 number of points from the blue cloud and N2 points from the magenta cloud. We must emphasize that that the number of points drawn is the same as the number of points in the original data and that the points are drawn with replacement.
5. We calculate the mean energy of the selected N1 points and separately for the N2 points. We call them 'E.TotalEnergy.EEMS.L0' and 'E.TotalEnergy.EEMS.Eco' respectively.
6. We repeat this operation for the 'L0' driver in the base corridor (the bottom panel in the chosen 'Eco' column of Figure II.1.4.14. Call it 'E.TotalEnergy.base.L0.'
7. Next, we compute the percent reduction in energy consumption as 100*(E.TotalEnergy.EEMS.Eco - E.TotalEnergy.base.L0)/ E.TotalEnergy.base.L0 and 100*(E.TotalEnergy.EEMS.L0 - E.TotalEnergy.base.L0)/ E.TotalEnergy.base.L0 respectively for the 'Eco' and 'L0' driver in the EEMS corridor.
8. We repeat steps 4–7 several times (e.g., 1,000) and produce an empirical distribution of the reduction in energy consumption. We pick the range covering the middle 2.5% to 97.5% to arrive at the 95% confidence interval for the expected reduction in energy. The boxplots of Figure II.1.4.14 are made from the empirical distribution so generated. As seen from the box plot, the trends are very encouraging and the spread in energy consumption benefits are tight especially as traffic volumes and vehicle interactions increase.

The mean reduction in energy (without the associated confidence interval of the boxplot of Figure II.1.4.14) is shown in Figure II.1.4.15. In summary, the energy savings realized in the simulation study are statistically significant. The next step was to down-select traces to be tested with real vehicles on a dynamometer that can bolster this claim.

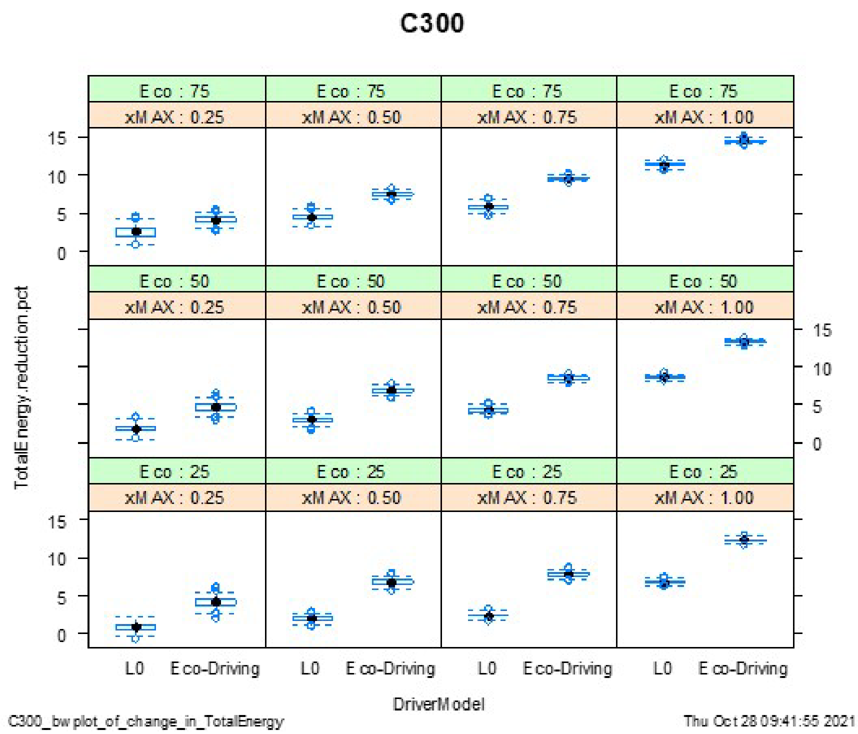

Figure II.1.4.14 Box plot of energy savings in C300 for default and eco driver in the EEMS corridor indexed by XMAX and ECO

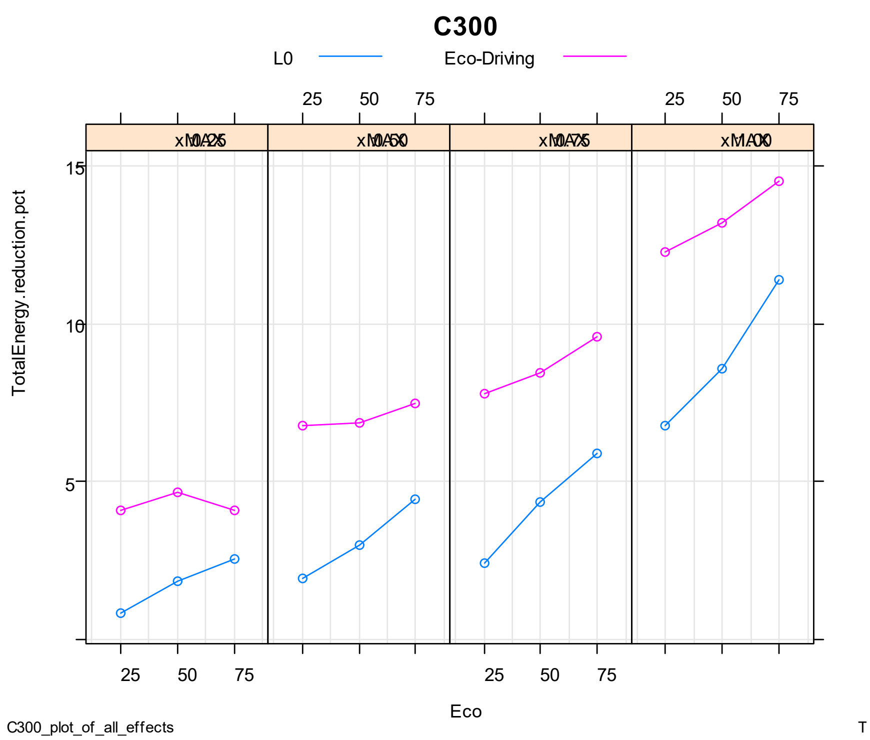

Figure II.1.4.15 Average energy eavings In the EEMS Corridor

Down-selection of traces to run on dynamometer

The analysis presented in the preceding section is based on thousands of simulations of the five vehicle powertrain models. These vehicle simulation models have been validated against the dynamometer data over the standard drive cycles such as UDDS, FTP75, HwFET, etc. However, the speed profiles in the Columbus corridor are different from the standard cycles and it is important that we validate a few of these energy numbers against dynamometer test data—to verify the relative change in energy consumption. The question is: which and how many points (recall that each point represents a trip or a speed trace) from each panel should we select to test on a dynamometer?

Note that a trip is approximately 20 minutes and there are 16 baseline and 12 eco-driving clouds. After evaluating multiple criteria, the team partitioned the trips based on trip time and energy. While trip time is an obvious parameter, trip energy consumption is a strong function of driver behavior, traffic conditions and powertrain type. Two trips with similar trip times can have very different energy consumption. The nonlinearity in total energy consumption of a powertrain is well captured in the powertrain models that were built earlier in the program. We chose three trips per cloud for a total of 84 trips per vehicle. Given periodic calibration of equipment, breaks for driver fatigue, and time taken to swap out vehicles, this was considered comprehensive and sufficient for validating the findings from simulation.

We used the standard technique of partitioning around medoids (PAM) to split each of the 28 clouds in Figure II.1.4.12 into three clusters and to choose the medoid of the cluster as its representative. A medoid is a member of the set as opposed to a centroid or an average point that may not be a member of the set. This is important because the desired output from the clustering scheme is a true drive trace from the simulation traces that can be tested on the real vehicle. The clusters established for the C300 projected to the principal components is shown in Figure II.1.4.16.

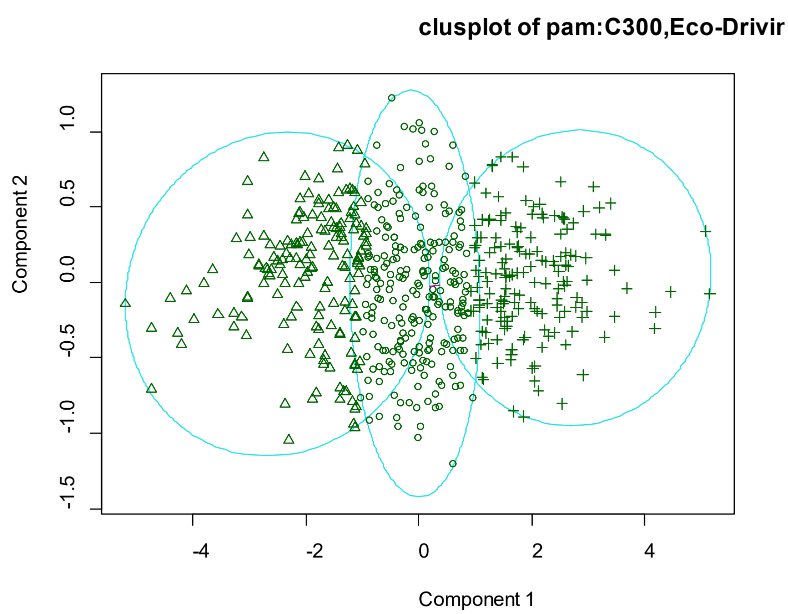

Figure II.1.4.16 Three clusters produced using the pam method; pam also produces a medoid for each cluster – the medoids become dynamometer cycles

The partitioning was repeated until the mean energy consumption and the mean trip time of the medoids are within 2% of the respective quantities for the original cloud.

Vehicle Testing

The team concluded testing the Chrysler 300 on the dynamometer. The order of the traces was randomized to remove any bias towards a scenario or group (baseline versus eco driver). Figure II.1.4.17 summarizes the comparison of test data with simulation data. The first subplot depicts the energy consumption of test vs the simulation on an x-y scatter plot. The second subplot shows that the traces being driven on dynamometer matched the traces in simulation. The third subplot shows a histogram of percentage difference between test and simulation energy consumption. The histogram peaks towards -3% to -4% error and a slight bias towards 0%, suggesting that the test results generally agree well with large-scale simulation data.

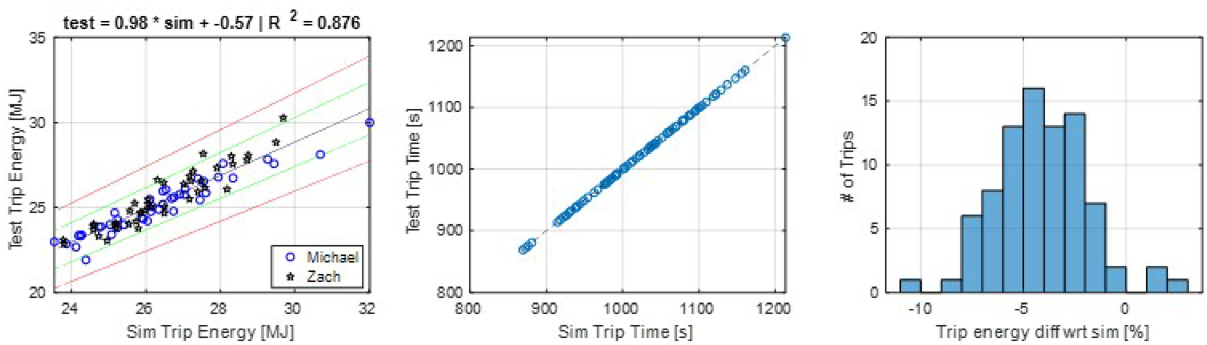

Figure II.1.4.17 Chrysler 300 dyno testing

Figure II.1.4.18 shows the test data for the Hyundai Elantra to date. Data aligns well with simulation predictions.

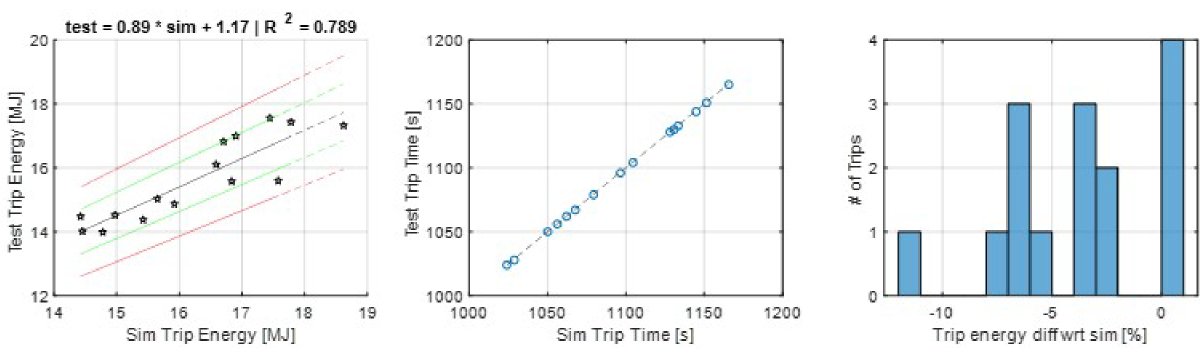

Figure II.1.4.18 Hyundai Elantra dyno testing

Reconsidering the attribute space for partitioning and selecting traces for dynamometer testing

While the initial partitioning based on trip energy and time worked well for the internal combustion engine-based powertrain types, the team noticed large variations in energy consumptions while testing the Prius Prime. Figure II.1.4.19 demonstrates the change in cumulative fuel consumption while running a triplicate test of the same driving trace because of marginal variations in starting SOC of the battery pack—69% through 71%. While this is still 'stock' operation of the vehicle, the difference in efficiency of the internal combustion engine (~35%) and the electric machines (~85%) significantly impacts the overall energy consumption. The focus of the program is to determine the energy consumption benefits due to differences in driving patterns—baseline driver versus eco-driving CAV. Therefore, this additional electrical energy needed to be accounted for and the clustering scheme was updated to accommodate such finer aspects of the powertrain.

Based on the 8.8 kW-hr battery pack capacity and making reasonable assumptions for the lower heating value of gasoline and efficiency of the gasoline engine in the Prius Prime, a simple calculation yields the equation:

$$1\ \%\ battery\ SOC \sim 16\ g\ of\ gasoline$$

The difference between beginning and ending SOC was calculated for each trip and all the energy calculations were normalized to a common fuel consumption reference. This accounts for the use of electrical energy during a trip.

From a clustering standpoint, we enlarged the original two-dimensional attribute space of net trip energy and trip time to seven dimensions:

1. Net ‘equivalent’ trip energy normalized to fuel
2. Trip time
3. Fuel consumption
4. Positive electrical energy (propulsion)
5. Negative electrical energy (regeneration)
6. Friction brake work (lost)
7. Mean trip speed.

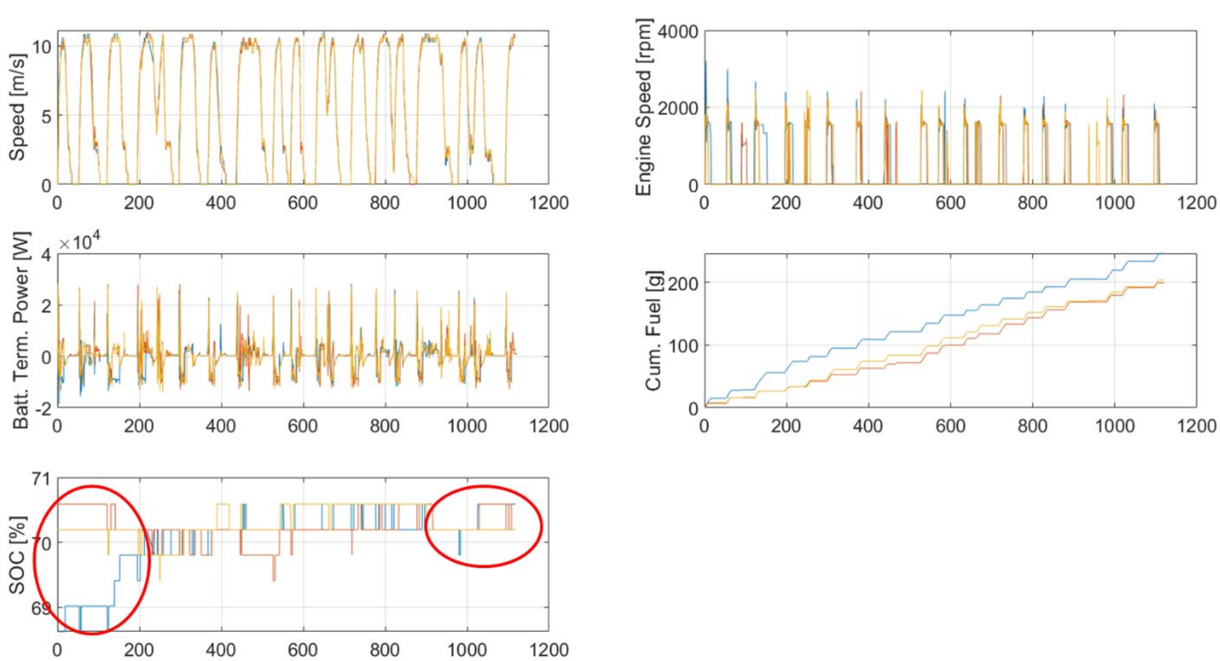

Figure II.1.4.19 Test data from Prius Prime for a triplicate test of the same drive cycle showcasing effect of initial state of charge on cumulative fuel

As before, we required that the mean of each of the seven attributes of the original cloud and of the selected subset be within 2%.

The team tested the Kia Soul EV and noticed a resolution issue in the CAN bus data that was causing challenges while calculating the total energy consumption. The original trips in the Columbus corridor are approximately four miles while the battery pack is capable of approximately 230 miles. We decided to run longer trips for the hybrid and electric vehicles to overcome the issue of resolution of electrical data. We decided to string the chosen trips in triplicate to make an hour-long trip. Given the limited resources allocated to dynamometer testing and focusing on high impact scenarios, the team decided to focus on the maximum traffic condition (rightmost column in Figure II.1.4.12) in baseline corridor (bottom panel; no EEMS technology), smallest available penetration of Eco (second from the bottom panel), and highest available penetration of Eco (top panel). This reduced the original 28 clouds to five as shown in Figure II.1.4.20. We selected five traces per cloud (instead of the original three) to achieve better coverage. In summary:

1. C300: three traces each from the 28 clouds—no change in original clustering
2. Elantra: five traces each from the five clouds at maximum traffic (xMAX=1.00; Eco= {00,25,75}; DriverModel= {L0, Eco-Driving}); trip length at original; traces chosen in the original attribute space
3. Model 3: five traces each from the five clouds at maximum traffic (xMAX=1.00; Eco= {00,25,75}; DriverModel= {L0, Eco-Driving})); each trace strung together in triplicate to make a longer trip; traces chosen in the enlarged attribute space
4. Prius: Same methodology as for Model 3
5. Soul EV: Same methodology as for Model 3

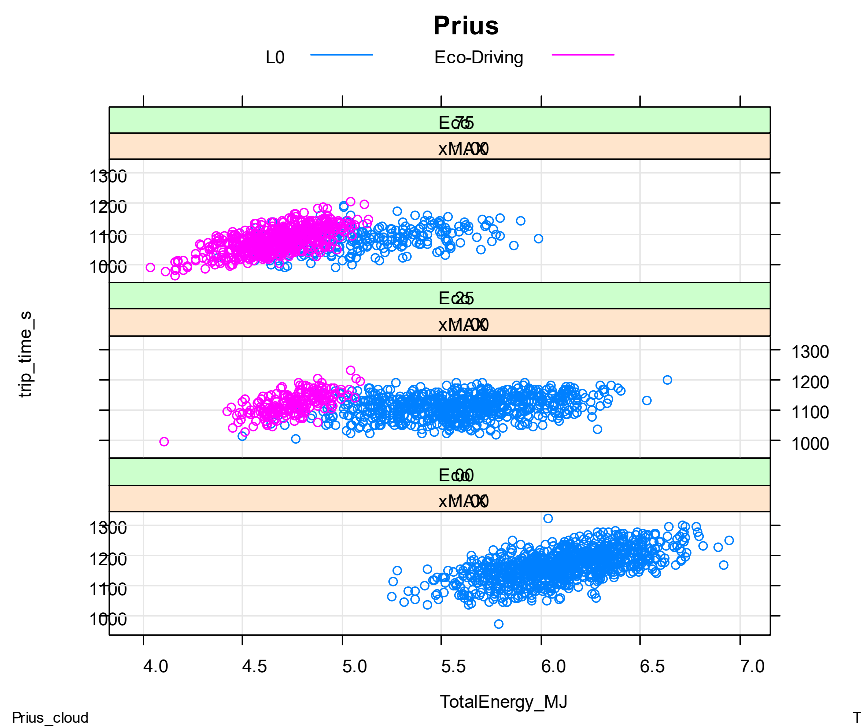

Figure II.1.4.20 Focus on a three (instead of 16) panels for dynamometer testing

Tech to Market (T2M)

Adoption model – vehicles and city equipment

The first part of the TEA model addresses the quantification of the potential fleet of vehicles susceptible to adopt the Vehicle System; it is based on the definition and selection of values for the main parameters of a city and its conurbation that impact the average number and length of intracity trips:

- Number of inhabitants
- Average daily number of intracity trips per inhabitant
- Split of these trips between cars, buses, and commercial vehicles
- Occupancy factors of vehicles
- Number of times the same vehicle is used (plays a role in terms of likelihood of adoption of Vehicle System)
- Area considered for these trips

Calculations are then developed that lead to:

- Average length and number of intracity trips for cars, buses, and commercial vehicles
- Addressable vehicles population to be system-equipped

The second part of this model evaluates the need of equipment for the city:

- Number of intersections
- Potential number of intersections to be equipped
- Portion of the traffic that is improved based on such equipment

Energy efficiency model

The fuel efficiency model first captures values directionally representative of the average reduction in energy requirement that can be expected across vehicles under nine different alternatives derived from combining.

- Three scenarios in terms of technology adoption: 25%, 50%, and 75%
- Three traffic conditions: light, medium, and heavy

The improvement in fuel efficiency is differentiated between vehicles equipped with the system and those not equipped, but still benefit from the improved flow.

The average energy requirement reduction is then applied to a few sample vehicles—with EPA city consumption sticker values ranging from 17 to 58 MPG for ICE/HEV passenger vehicles, and BEV with city values higher than 100 MPGe—to estimate the yearly savings based on miles travelled and fuel (gasoline and electricity) prices.

If needed, the calculations of savings could be made on specific vehicles. The outcome of the fuel efficiency model is used in the financial model to compare these benefits for vehicle owners against the expenses incurred with the system.

Emissions model

The emissions model leverages the improvements observed in terms of energy requirements when a fraction of vehicles in the traffic is equipped with the System to expand them into potential benefits in terms of CO_2 emissions as well as pollutants NOx, CO, and particulate matter (PM) emissions. The approach followed for the quantitation is two-pronged:

- Identification of the reduction in energy requirements, as per energy efficiency model above
- Translation of reduction in energy requirements into their impact in terms of reduction of emissions

Note that this two-pronged approach parallels the method employed in The Real Urban Emissions (TRUE) Initiative launched by ICCT [5] to measure real-world emissions in more than 40 cities.

Benefits again will be linked to both system-equipped vehicles, and non-equipped vehicles which also benefit indirectly.

Proper translation will require a precise estimate of the sensitivity of the quantity of pollutants emitted per quantity of fuel consumed (expressed in grams of pollutants per kilogram of fuel) as a function of the specific power required on a representative city cycle (kW per ton of vehicles). The reduction in energy requirement will be linked to the model above.

In most cases this sensitivity is a monotonic, positively sloped function of the specific power, but not all vehicles necessarily behave in the same way. Dispersion may exist across model years and could eventually be exacerbated in the case of vehicles that narrowly target specific duty cycles, resulting in islands of low emissions surrounded by cliffs of higher emissions.

Financial model

The financial model encompasses:

- A summary of the costs that a vehicle owner would bear on average per year to benefit from the Vehicle System, and comparison with the savings resulting from lower energy use.
- A summary of the investments and costs experienced per year at the city level to reduce emissions, compared to the improvement in emissions.
- A societal grand total, including the "free ride" benefits provided to vehicles not equipped with the system.

Conclusions

The focus of this budget period was on software-in-the-loop validation and vehicle demonstration on a chassis dynamometer. The team finished the large-scale simulation study and is on track to complete the chassis dyno demonstration. The team will transition to track testing in budget period 3. From a T2M perspective, the team completed public sector engagement surveys, market forecasts, competitive analyses, and cost-performance model.

Key Publications

1. Manuscript submitted for SAE World Congress 2022 – "Quantifying System Level Impact of Connected and Automated Vehicles in an Urban Corridor"

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5. https://theicct.org/publications/on-road-emissions-paris-201909

Acknowledgements

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II.1.5 Transit-Centric Smart Mobility for High-Growth Urban Activity Centers: Improving Energy Efficiency through Machine Learning

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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. In Boston and Chicago, for example, the average driver loses over 145 hours per year in traffic congestion, eroding mobility, wasting fuel, and accruing costs exceeding $7 billion and $4 billion, respectively. Boston's Seaport District, with skyrocketing commercial development, 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 based on state-of-the-art machine learning (ML) and robust optimization methods (Figure II.1.5.1). 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, transit ridership, and energy efficiency.

2. Building an Integrated TSMS with Robust Optimization (RO), Reinforcement Learning (RL), and Deep Learning (DL) – 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 research team will deploy field experiments to test the proposed technologies in Boston's Seaport District - Logan Airport area and Chicago's West Loop 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.

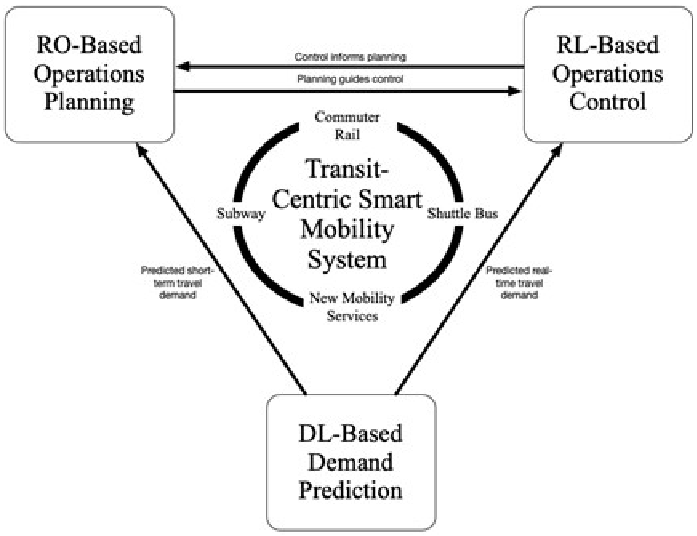

Figure II.1.5.1 Framework of transit-centric smart mobility system (TSMS)

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. 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.

2. 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.

3. 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.

Results

Delay Caused by Foreign National Processing

The MIT team applied for five months' No Cost Time Extension (NCTE) for the project. The five-month extension compensates for the delay in the foreign national processing (FNP). The team applied to extend the initial ending time (12/31/2021) of BP1 by five months to 05/31/2022. All the other aspects of the project, including the scope and duration of BP2 and BP3, remain the same as the initial SOPO. Although the project started on October 1, 2020, the researchers in the MIT&NEU team are not allowed to work on the project until the approval of the FNP. Specifically, the team submitted the FNP application for two MIT researchers (Shenhao Wang and Qingyi Wang) in October 2020, and the applications were approved three months later (Dec 2020). The team submitted the FNP application for Joseph Rodriguez (from NEU) in February 2021, and his application was approved by the end of August 2021. The team submitted the FNP application for Xiaotong Guo (from MIT) in February 2021, and he was just allowed to formally work on the project through the recent cooperative agreement between MIT and DOE in September 2021. In short, most of the research team experienced about 4-6 months' delay due to the FNP.

Data Collection, Management, and Sharing

The MIT team target to collect a *relatively complete* data set for the Chicago area within the scope of the project. Due to the nature of this research, the research team paid close attention the data sets related to human dynamics and urban mobility, along with the pertinent topics such as energy consumption, air pollution, economic growth, and other impacts of human behavior. The final goal is an Integrated Smart Chicago Data Set, which can be the foundation for a multitude of research topics within the DOE project.

The research team made the data collection efforts public. The complete data collection efforts can be found at https://github.com/sunnyqywang/Chicago-Integrated-Data-Repo. The repository has incorporated the contents, resources, and remaining questions for 14 different data sources, including (1) meta data set, (2) socio-demographics from Census, ACS, and CTPP, (3) GIS shapefiles, (4) mobility flow, (5) spatiotemporal ridership, (6) general transit feed specification (GTFS), (7) general road network flows, (8) travel survey, (9) images, (10) OpenStreetMap and Point-of-Interests, (11) mobility-related data (COVID, air pollution, energy), (12) web scraping data, (13) private data providers, and (14) others. We already used socio-demographics data, GIS shapefiles, spatiotemporal ridership, GTFS, travel survey, images, and point of interest data in the technical module for demand analysis.

Travel Demand Prediction with Deep Learning (DL)

This technical module leverages machine learning for demand modelling. Because of the geospatial nature of the census tracts and transit lines, graph neural networks (GNN) are used to estimate demand. A graph structure naturally arises from treating the census tracts or transit stations as nodes and the geospatial relationship between such entities as edges. Spatial relationships are quantified through graph convolutions between the nodes and edges for each snapshot in time, and the time series can be modelled using variations of recurrent neural networks (RNN). Since an RNN+LSTM structure has become quite dominant in demand predictions, and often achieves the state-of-the-art performance across multiple scenarios. This research lays its foundation on the deep learning-based methods to boost the predictive performance.

The demand modelling work started with the prediction of the short-term transit ridership with uncertainty measures for the subway stations of the CTA network. A truncated mean-variance estimation graph convolutional neural network (TMVE-GCN) was designed for prediction. The time series of the station's own recent demand, and the recent demand observed from other modes (bus and TNC) in the catchment area, serve as the primary explanatory variable. Schedule information, weather, socio-demographics are also incorporated into the modelling framework to improve predictive performance. In addition to the prediction of short-term demand, the contribution of the work lies in quantifying the statistical confidence of such predictions by outputting both the mean and the variance of the demand prediction. The TMVE-GCNN can achieve accurate prediction intervals without sacrificing the quality of the mean prediction in both the pre- and post-COVID periods. Figure II.1.5.2 shows two prediction interval measures: mean prediction interval width (MPIW) and prediction interval coverage probability (PICP). The prediction interval widths (y-axes) are plotted on different scales due to ridership decline during COVID period. The model was trained to produce a 95% prediction interval, training instances of GCN models were able to achieve the most accurate coverage probability while the prediction interval width was reasonably narrow compared to the benchmark models—last week and weighted least squares (WLS).

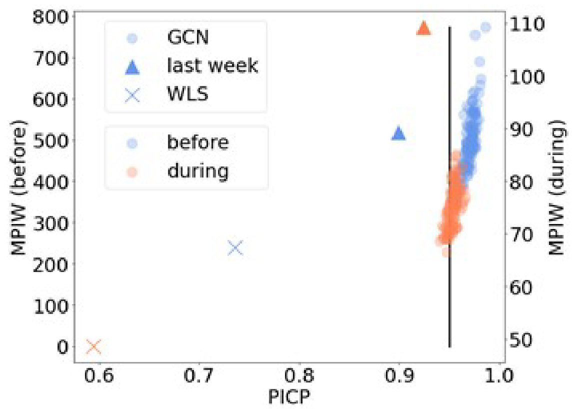

Figure II.1.5.2 Evaluation of uncertainty quantification for transit ridership prediction

The TMVE-GCN model also achieves high-quality transferability performance, as evidenced by Table II.1.5.1. The first row shows the results obtained from training and testing the models for the post COVID period, and the second row shows the results obtained from training the models on the pre-COVID data and testing on the post-COVID data. The two scenarios use the same testing set. The model performance stayed relatively high even with the ridership significantly reduced after COVID-19 hits. Likelihood worsens by less than 3% and root mean squared error stayed the same. With respect to prediction intervals, the model becomes a little more conservative when forming prediction intervals when transferred, achieving 2.8% more coverage with width increase of 4 passengers.

Table II.1.5.1 TMVE-GCN Performance for Pre- and Post-COVID Periods

Train Period	Test Period	Composite	Mean	Prediction Interval	
		Negative Loglikelihood	RMSE	PICP	MPIW
After	After	70.44	25.58	0.9616	80.89
Before	After	72.65	25.57	0.9895	94.99

Real-Time Operations Control with Reinforcement Learning (RL)

The team targets to design a framework to experiment transit operational control using a reinforcement learning (RL) approach. As opposed to analytical methods for control decisions, RL develops a control policy from experience, guided by a reward function defined according to the objectives. This experience is generated from a transit simulation model that captures the stochastic nature of passenger demand and travel times.

The effectiveness of the approach is shown in a real-world context. In the first scenario we model a variation of an existing bus route in a rapidly growing business hub in the Boston area, in which we convert the route from a fixed-stop operation to a flexible-stop operation. The flexibility allows for a larger service area that could increase ridership in the low demand period of day and improve accessibility, albeit a difficult challenge from a control perspective, since the service must respond to real-time requests for route deviations. The RL problem is thus defined by the local state, the number and location of pickup and drop off requests at the deviated stops, the action set, which deviated stops to serve, and the reward function which is based on a penalty for added travel time on board and the benefit of serving more passengers. The RL policy, referred to as Parallel Q-learning (PQL), is compared against a rule-based policy applied in similar services, deciding which requests to serve based on maximum delay threshold, referred to as Smart Greedy (SG). Both strategies were tested in a simulation episode of a 3-hour peak demand period (75 pax/hr.) with 15-minute scheduled headways. In Figure II.1.5.3, we demonstrate the decrease in average trip departure delay from operating the policy resulting from RL training. The outbound direction shows similar performance given that it is the high-demand direction.

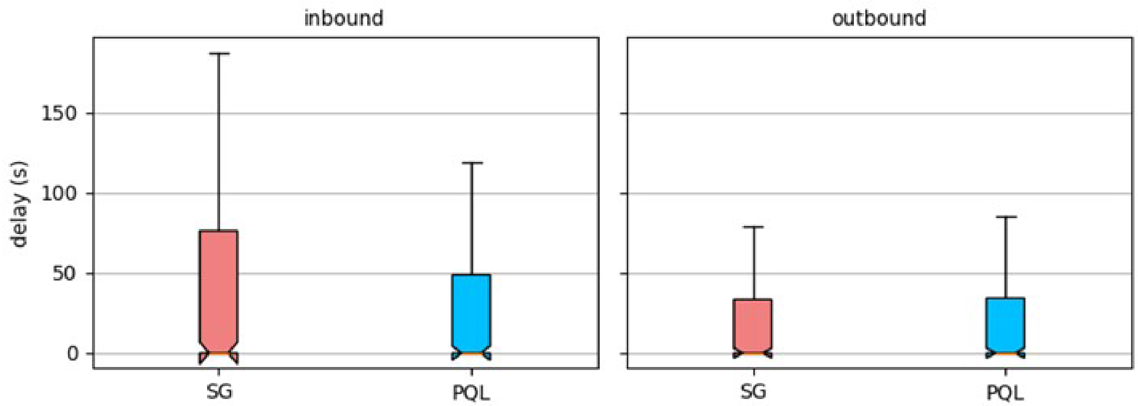

Figure II.1.5.3 Average delay comparison between Smart Greedy (SG) and Parallel Q-Learning (PQL)

Following the policy, although managing to save travel time delays, it decreases the request rejection rate by 5%, as shown in Table II.1.5.2. Moving forward, the aim is to extend the framework to a deep learning-based computation of the value of the action, which allows to generalize the RL policy to more complex state definitions and add the option of cooperative strategies between buses in service.

Table II.1.5.2 Comparison of % Requests Rejected

	SG	PQL
Received	42	47
Rejected	10	9
% Rejected	24%	19%

Short-Term Operations Planning with Robust Optimization (RO)

The main problem in this module is referred to as the transit network frequency setting problem (TNFSP) for a single transit line considering different operational patterns and vehicle types. Meanwhile, passenger demand is versatile in the transit system especially during the post-COVID time. Remote working has permanently changed commuters' travel behaviors and brought them a considerable degree of temporal and spatial flexibility. To incorporate demand uncertainty into the TNFSP, we propose two models using two different approaches: stochastic programming (SP) and robust optimization (RO). The SP method serves as the benchmark which generate the best transit schedules given the expected demand scenario, while the RO approach produces the transit schedules against the worst-case demand scenario, which performs better when demand is highly uncertain. At the current stage of the RO planning module, we have constructed the proposed models and test the model performances with synthetic dataset. The next step is to pick a transit line from Chicago and test the model performances under the real-world scenario. Performances will be compared with the current schedule under a simulation.

Integrated System

A preliminary effort has been made to integrate the three modules, which can be accessed publicly at the Github repository https://github.com/joerovar/transit-centric-smart-mobility-system. The demand prediction module outputs a time-dependent OD demand distribution $OD^{predicted}$, which the robust optimization module uses to find an optimal scheduled headway H. Lastly, the demand and service data inputs into the RL module for training the agent and upon testing, to store the series of outputs V on the Level of Service (LOS), which include measures of regularity, delay, ridership, and travel time. The algorithm has been applied on CTA's route 20 to evaluate the base case scenario with no control strategies applied, the traditional even-headway holding strategy, and the deep reinforcement learning based holding/no-boarding strategy. Some preliminary improvements seen are increased uniformity in bus loads, which is a result of improved regularity in the service and translates into more reliable wait times for the passengers and less crowding in the buses.

Conclusions

The MIT research team has successfully collected the main data necessary for the preliminary modeling efforts. The data sets include spatiotemporal transit ridership, socioeconomic information from the census, GTFS, and high-dimensional imagery from Google API. The data is used for developing the three technical modules. The DL-based demand prediction module uses the graphical neural network to capture the network nature of the transit system. The research team innovates on the integration of uncertainty into the standard mean value prediction and the incorporation of urban imagery into the classical demand analysis in two different scenarios. The team demonstrates that the GNN based approach could describe the uncertainty pattern of the transit ridership with enhanced predictive performance in comparison to the benchmark models. Regarding the RL-based transit control, the team has built up the light simulation environment to simulate a route in the West Loop area in Chicago and provided a baseline PQL algorithm to reduce the transit waiting time. The current performance of the PQL approach can outperform the benchmark smart greedy method. The team has also started to integrate the three modules into a system, which can provide functioning interfaces across the three technical modules and the MEP computation from NREL.

Key Publications

1. Q. Wang, S. Wang, H. Koutsopoulos, and J. Zhao, "Uncertainty quantification of spatiotemporal travel demand with graph convolutional neural networks", (*Submitted* to: IEEE Transactions on Intelligent Transportation System.)

2. J. Rodriguez, H. Koutsopoulos, S. Wang, and J. Zhao, "Operational Control of Flexible Feeder Transit with Multiagent Reinforcement Learning", (*Accepted for presentation* in Transportation Research Board 101st Annual Meeting.)

II.1.6 CIRCLES: Congestion Impacts Reduction via CAV-in-the-loop Lagrangian Energy Smoothing (The Regents of the University of California)

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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 (adaptive cruise control (ACC), ecodriving, etc.). These two families of control were not co-designed and are not engineered to work in coordination. Recent studies have shown 1) limitations of controls, and even 2) 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 want to demonstrate 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 focus 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 will result in energy gains exceeding 10% for all vehicles on the road, through automation of less than 5% of the vehicles in the flow. 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 we expect (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 is 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 will develop control algorithms using a variety of techniques ranging from classical control theory to deep reinforcement learning (deep-RL), which will allow our control vehicles to cooperatively smooth stop-and-go waves in a real highway environment with live traffic. The team has subdivided into cross-collaborative and cross-functional teams, each spanning multiple institutions and time zones:

- In Situ Field Testing; Primary Contributors: all institutions
- I-24 Testbed Development; Primary Contributors: Vanderbilt & TDOT
- Computer Vision; Primary Contributor: Vanderbilt
- Traffic Flow Modelling; Primary Contributors: all academic institutions
- Energy Modelling; Primary Contributors: Temple, Toyota, & Berkeley
- Control Algorithm Design; Primary Contributors: Rutgers, Berkeley
- Safety; Primary Contributors: all academic institutions
- Hardware; Primary Contributor: Vanderbilt, Arizona, & Berkeley.

Approach

The work focuses on mobile actuation of multi-lane traffic. Our approach is thus to 1) establish the minimum sensing and connectivity needs required 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 further advance the development of high-fidelity control strategies. Our approach to achieve our objectives includes

1. Developing mathematical models of the traffic, to enhance understanding of the predictability of stop-and-go waves, with careful investigation of lane changing models
2. Designing sensing systems and estimation algorithms to detect the traffic state using on-board vehicle sensing and/or infrastructure sensor networks
3. Designing control and machine learning algorithms to robustly dampen waves or prevent their amplification, by combining lateral and longitudinal control of CAVs

4. Performing software verification of the models, sensing systems, estimation, and control algorithms in simulation and on-board CAVs

5. Investigating intelligent agent design constructs for human–autonomous collectives in mixed autonomy environments.

Results

In-Situ Field Testing. During the week of August 2–6, 2021, we carried out medium-scale field operational tests on Monday, Wednesday, and Friday (aka the “VanderTest”). We conducted tests with 11 cars; all were instrumented to record driving data (e.g., radar tracks, speed, GPS position) and four were specially instrumented to run our custom-designed controller when cruise control was activated. The tests allowed us to measure the cumulative effect of controllers in highway traffic, while also preparing us for the logistical and technical challenges of executing the much larger demo in Budget Period 3.

Figure II.1.6.1 Photographs from the VanderTest. (Left) Our observation team reviewing video footage of test vehicles passing a TDOT camera. (Right) Smyrna Police escorting a platoon of test vehicles from the staging area to the I-24 on-ramp.

I-24 Testbed Development. Continued development of the I-24 testbed (aka I-24 MOTION) has been focused on designing and commencing construction on the next four miles of the testbed to expand on the success of the prototype validation system constructed in 2020. Design of the four-mile phase (to be constructed in 2021–22) commenced in Q1 2021 and completed in Q3 2021. The project was released for bids from contractors in September, with project letting in October. A final selection of project contractor is pending at the time of writing this report, but no issues are anticipated for making the award. We anticipate the remainder of 2021 to include: a “notice to proceed” given to the selected contractor by TDOT, a pre-construction meeting taking place, and work commencing on installation sites. Major design elements remain unchanged from the prototype system, with some small alterations to accommodate site constraints, improved vantage points and views, and updated camera models.

Accompanying the field infrastructure is a simultaneous design and deployment of the cyber infrastructure for processing data. This consists of network equipment for transporting data from the camera system to the central processing site at Vanderbilt University; servers for processing video data; data storage equipment for buffering video and storing trajectory data and system metadata; and data distribution infrastructure for making data available to other researchers. All this equipment—~20 servers in total—will be hosted in the Vanderbilt data center and operated 24/7/365. Centralized hosting allows for greater system integrity and resilience, easier system management, and professional administration and maintenance of hardware systems.

The deployment of the cyber infrastructure has begun on the networking front. A dedicated fiber optic network connection between the Tennessee Department of Transportation and Vanderbilt is constructed and currently being activated. Purchasing of servers will occur in December 2021, allowing this hardware to be installed in Q1 2022. This timeline will coincide with the integration and testing of software systems for trajectory processing in Q1–Q2 2022.

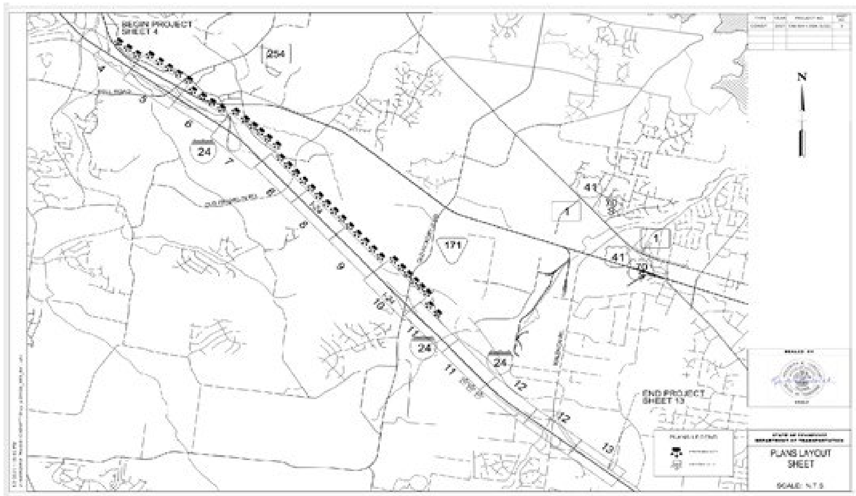

Figure II.1.6.2 Overview of I-24 MOTION 4-mile phase, taken from the official, PE-stamped design plans.

Computer Vision. Major advancements on computer vision tracking of vehicle locations have been made in 2021. The innovations in fast tracking algorithms from 2020 using object localization steps have been extended to operate on multiple adjacent cameras, which further reduces processing requirements and maintains more consistent vehicle tracks across space and time. Additionally, vehicle detection and localization neural networks have been trained to produce three-dimensional bounding boxes, thereby capturing the footprint of the vehicle on the roadway and its dimensions. This leverages information about the orientation of the vehicle, which must be parallel to the roadway direction of travel.

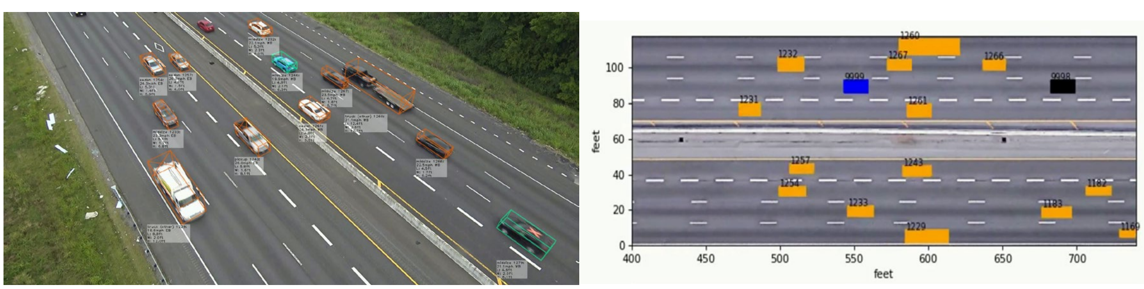

Figure II.1.6.3 (Left) Demonstration of object tracking with 3-dimensional bounding boxes and annotations of vehicle speed and ID. Vehicles with green bounding boxes were part of the VanderTest. (Right) Vehicle bounding boxes translated to roadway coordinates. Test vehicles from left figure shown in blue and black.

Vehicle tracking algorithms will be built into production-ready processing software for running on the I-24 MOTION compute cluster. This will include utilities for logging performance, anomalous data, and system status to continually improve trajectory processing. Video will not be stored as part of the trajectory processing, except for the purposes of algorithm validation and training.

Traffic Flow Modelling. While building our SUMO I-24 model (porting learnings from our prior I-210 model, adding new features, calibrating speeds/inflows, generating stop-and-go waves), we collected actual driving trajectories; we quickly realized that the actual traffic flow exhibited distinctly non-periodic waves, contrasting the strong periodicity in our simulations. To avoid a significantly larger simulation to capture this effect (computationally intractable and out-of-scope), we collected 60+ I-24 trajectories and built a single-lane simulation platform that can playback those driving trajectories and forward-simulate trailing vehicles with user-defined controllers. Notably, this solution is easily scalable to build models of other freeways.

This simulation platform allowed us to quickly train and test new controllers, including the one used at the VanderTest. In the subsequent months, we have been implementing an empirically motivated lane-change mechanism, following on the work from [3], to stochastically insert/remove vehicles from the simulation.

Energy Modelling. In Budget Period 2, the team has focused on a validation process for the developed hierarchy of models from Budget Period 1 (please refer to last year's report for details). Based on initial validation against Autonomie, a significant thrust has been the refinement of the energy models, in particular: further development relevant for stop-and-go waves on the level of gear scheduling and torque convertor in first gear; and adding road grade and fuel cut factors into the simplified model.

In collaboration with Toyota, systematic experimentation on a physical dynamometer was carried out with a model RAV4 vehicle. Measurements from these experiments are used for detailed validation in a controlled setting for the model hierarchy and Autonomie. The validation results are still work in progress, but it should be noted that Autonomie itself has some noticeable deviations from the dynamometer measurements. Preliminary validation results across the hierarchy of models show that, on the level of total fuel consumption, an average variability in the range of 4% was found.

Control Algorithm Design. We have approached control algorithm design with a variety of methodologies. Here, we highlight a few approaches that are actively being developed for the Budget Period 3 demo.

Microcontroller. The "Microcontroller" (micro-model-based controller) is based on (1) deriving an ideal target speed for the road, (2) adjusting this speed with respect to the local situation, (3) applying a safety mechanism on top. This controller outputs a commanded velocity that is then converted into an ego acceleration. In Budget Period 2 we optimized the parameters of Step 2 to compensate for the estimation error in Step 1 (for which we compared several options). We added variants of this velocity-based controller with several options depending on the needs and to increase its robustness to hardware uncertainties. This controller was tested in simulation first, and preliminary studies showed an effective 10% fuel reduction for a 5% penetration rate.

We also defined a new version of the controller that is intrinsically acceleration-based and directly outputs an acceleration. This intends to leverage the advantage of having direct access to acceleration and allows a better anticipation of the lead car deceleration while remaining very robust. This controller is still in progress and should allow smoother management of the space gap and be more user-friendly than its velocity-based counterpart using only the FollowerStopper (FS) wrapper safety mechanism for gap management.

Optimal Trajectory. The optimal trajectory approach aims to find the best possible velocity controller of the given (a priori) lead vehicle's trajectory. The results of the approach are optimal with respect to an objective function that accounts for fuel consumption, variations from an ideal desired velocity, and safety. The setup of the problem consists of a lead vehicle with a known (future) trajectory followed by our controlled vehicle and several human driven vehicles (IDM). With this setup, we pose an optimization problem to find the optimal velocity at every time step along the trajectory. The optimization is solved using a gradient based approach in which gradients are explicitly supplied to the optimizer, significantly reducing computation time.

The optimal velocity controllers we get using the approach are open-loop controllers that rely on information about future states of the system. Thus, they are not suitable for direct deployment. However, they can be used as part of another such as the imitation learning or the model predictive control approaches described below.

> Imitation Learning. We previously found success using Imitation Learning (IL) on the I-210 model by mimicking the FS (with downstream knowledge). IL helps to remove explicit dependency on non-local sensing, producing a decentralized controller that does not require feedback from non-local sources. Simulation results on I-210 indicated its ability to improve the energy-efficiency up to 15%

with AV penetration rates as low as 5%. Inspired by this success to bridge the gap between promising theoretical strategies and realistic limitations in sensing, we aim to apply IL on Optimal Trajectories along I-24, thereby removing the approach's dependency on future knowledge. By treating the trajectories as our expert, we will develop a controller that only takes current information.

Model Predictive Control. The model predictive controller (MPC) is designed to efficiently follow a lead vehicle and to attenuate any velocity oscillations that a lead vehicle may produce. In its current form, it is an optimal control adaptation of Kerner's controller [4], which aims to follow the lead vehicle's velocity without keeping a constant time gap (provided it is safe and socially acceptable), to dampen velocity variations. The controller is implemented by solving a linearly constrained quadratic programming problem in a receding-horizon manner. With a 20 Hz update frequency, we predict the lead vehicle will keep its acceleration constant for the next 0.5 seconds. Our preliminary numerical study has indicated that the MPC is effective: 1) it is able to attenuate the lead vehicle's oscillatory trajectory in mixed-autonomy traffic; 2) with a 5% penetration rate, it achieves approximately 10% saving in fuel rate (gal/h) 200m upstream of a shockwave.

Single-Agent Reinforcement Learning. Leveraging the trajectory-following simulator (see Traffic Flow Modelling), we trained a vehicle (following behind replayed real trajectories) controller to smooth either itself or a platoon of following vehicles (IDM). We train the controller using reinforcement learning (RL) methods, first by designing a Partially Observable Markov Decision Process (POMDP) that is feasibly implementable on a real vehicle, then using an algorithm such as the Proximal Policy Optimization (PPO) to train the controller to optimize a reward function (or objective). It is essentially trained by gradient ascent [5] to maximize a reward function including an energy performance term and a safety term.

Safety. To build safety into the development and evaluation of our autonomous vehicle controllers, our approach has relied on the following threads:

Vehicle operators should be able to rely on safe execution of any energy-smoothing controller in nominal conditions. During the previous year, we explored the safety of the FS to avoid forward collision through Hamilton-Jacobi reachability analysis. Through that effort, we produced results that were able to determine the safe sets of the FS to serve as a supervisory controller. The reachability sets were able to show safe behavior at low speeds, but that at higher speeds its time gap would violate safe driving norms. This limitation was overcome through the synthesis of an updated supervisory controller that uses existing ego vehicle speed (not just relative speed of the lead vehicle) to influence the output velocity. With this update, the FS can be verified at any speed to obey these time gap following criteria (see F.-C. Chou et al. in Published papers).

Energy-smoothing controllers should be able to operate in regions outside their training region, which may require presence of a supervisory controller. With a safe supervisory controller, it is possible to execute RL-trained controllers, even when they are operating in regions not initially in their training regimes, if the supervisory controller can mitigate inputs seen as unsafe. This permits the energy-smoothing controllers to operate even if within a region in which they have not been trained, and the supervisory controller takes over *only* when safety margins are breached.

A safety controller should understand whether nominal conditions have been suspended, and thus that the vehicle operator should resume manual control. *In situ* operation of the vehicles in traffic means that a significant number of events could occur which should supersede nominal operations. Our controllers do not execute under two criteria:

1. if engaged and a vehicle cuts too closely in front of the ego vehicle, the controller reverts to the operator with an audible "ding" to indicate that cruise control is not available; and

2. if disengaged, the system may decline to engage if it would result in immediate braking from a controller, or if there is no lead vehicle in evidence

Safety controllers should be analyzable for nominal traffic conditions. Parameters initially selected for safety margins were too conservative for deployment in traffic flow, if based simply on best practices. Taking this into account, these parameters were derived from the IDM in simulation, producing a safety controller that could be deployed in nominal conditions. Referring to Figure II.1.6.4, the nominal traffic conditions (based on IDM) frequently were inside regions of the FS where braking would be required, regardless of the commanded values from any energy-smoothing controller. We recalibrated the FS to more realistically permit the energy-smoothing controllers to execute across a wide array of inputs. The final tuned controller was deployed in the VanderTest and has continued to be used for *in situ* validation in I-24 driving in the period since.

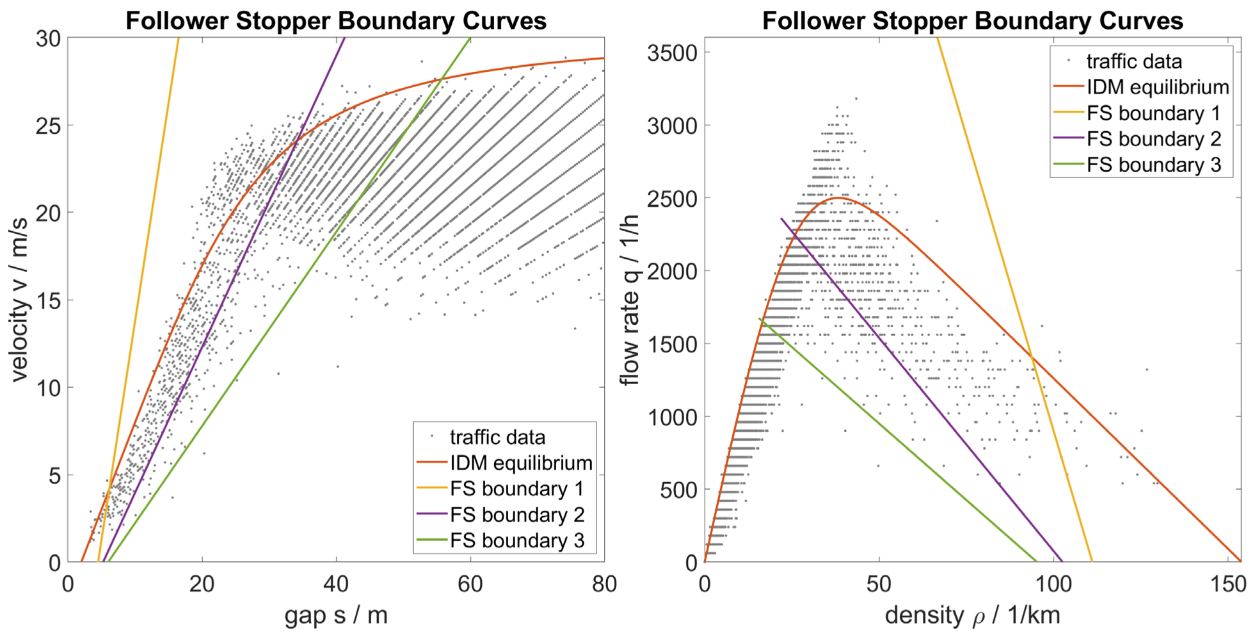

Figure II.1.6.4 (Left) With original gains for the FS, the safety controller will be reducing the speed of the vehicle when encountering normal traffic conditions, limiting the effectiveness of any energy-smoothing controller. (Right) New gains reserve safety margins for areas of the phase space where normal traffic is not typically observed.

Hardware. Hardware interfaces used in the VanderTest continue to integrate more features regarding better safety supervisory controllers, better system characterizations, and additional supported hardware. Implementation for *in situ* deployment continues to rely on comma.ai data ports that interface with a Raspberry Pi computer. At the lowest level, our libpanda package provides the raw CAN data reading and CAN data spoofing required for mimicking the cruise controller module. Another package (can_to_ros) interfaces libpanda with ROS. Some low-level safety checking nodes for events like run-time value-based verification are written in C++ ROS. The ROS-based interface allows the rapid deployment of controllers designed using Simulink through code-generation. Simulink has been used to develop further low-level controllers like a PID controller that effectively translates velocity commands to acceleration commands. Finally, the supervisory controller ensures that velocity commands are within a safe region based on the distance to the lead vehicle and speed of the ego vehicle. Open-source packages document the various ROS topics reported by can_to_ros. We have also outlined the specification of each low-level controller so that designers can understand the various safety regions that may automatically disengage their controllers during data collection.

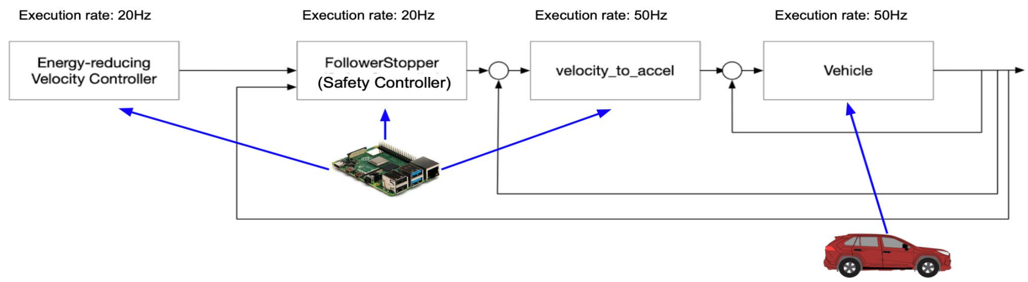

Figure II.1.6.5 An outline of the interfaces highlighting how custom controllers fit within the hardware platform.

Conclusions

As of this writing, we have completed two of four of Budget Period 2's milestones. For Milestone 2.2, we executed numerous small-scale tests on control vehicles in the months, weeks, and days leading up to the VanderTest. For Milestone 2.4 (the Go/No Go milestone for Budget Period 2), the VanderTest showed our ability to execute a medium-scale field test on the testbed and gather the data needed to quantify our impact on system-level fuel savings.

Milestones 2.1 and 2.3 are still work in progress. For Milestone 2.1, we have a simulation of the testbed environment that achieves (by design) virtually zero percent RMSE speed error. We are nearly complete implementing a stochastic lane-change feature based on empirical data, which we feel is important to truly call this milestone complete. For Milestone 2.3, we have collected controlled experiment data from vehicle dynamometer tests (executed by project partner Toyota). The data is being carefully analyzed to determine systematic shortcomings of our energy models and used for model calibration in the remaining months.

Key Publications

1. D. Gloudemans, W. Barbour, N. Gloudemans, M. Neuendorf, B. Freeze, S. ElSaid, and D. Work, "Interstate-24 MOTION: Closing the Loop on Smart Mobility," Workshop on Design Automation for CPS and IoT (DESTION 2020) Co-located with IEEE/ACM CPS-IoT WEEK 2020, April 21, 2020, Sydney, Australia (virtual).

2. F.A. Chiarello, B. Piccoli, and A. Tosin, "Multiscale Control of Generic Second Order Traffic Models by Driver-Assist Vehicles", SIAM Multiscale Modeling and Simulations.

3. E. Vinitsky, A. Kreidieh, N. Lichtlé, A. Velu, K. Jang, J. Lee, T. Ardoin, J. Carpio, S. Almatrudi, B. Zhao, B. Nguyen, and A. Bayen, "Energy Optimization of Mixed Autonomy Traffic at Scale using Deep Reinforcement Learning", poster presentation at Berkeley Artificial Intelligence Research/Berkeley Deep Drive Fall Workshop 2020.

4. S. Elmadani, M. Nice, M. Bunting, J. Sprinkle, and R. Bhadani, "From CAN to ROS: A Monitoring and Data Recording Bridge", in The Workshop on Data-Driven and Intelligent Cyber-Physical Systems, 2021.

5. M. Bunting, R. Bhadani, and J. Sprinkle, "Libpanda - A High Performance Library for Vehicle Data Collection", in The Workshop on Data-Driven and Intelligent Cyber-Physical Systems, 2021

6. P. Ngo and J. Sprinkle, "Lightweight LSTM for CAN Signal Decoding", in The Workshop on Data-Driven and Intelligent Cyber-Physical Systems, 2021.

7. J.W. Lee, G. Gunter, R. Ramadan, S. Almatrudi, P. Arnold, J. Aquino, W. Barbour, R. Bhadani, J. Carpio, F.-C. Chou, M. Gibson, X. Gong, A. Hayat, N. Khoudari, A.R. Kreidieh, M. Kumar, N. Lichtlé, S. McQuade, B. Nguyen, M. Ross, S. Truong, E. Vinitsky, Y. Zhao, J. Sprinkle, B. Piccoli, A.M. Bayen, D.B. Work, and B. Seibold, "Integrated Framework of Vehicle Dynamics, Instabilities,

Energy Models, and Sparse Flow Smoothing Controllers", in The Workshop on Data-Driven and Intelligent Cyber-Physical Systems, 2021.

8. Y. Wang, G. Gunter, M. Nice, M.L. Delle Monache, and D. Work, "Online parameter estimation methods for adaptive cruise control systems," Transactions on Intelligent Vehicles, vol. 6, no. 2, pp. 288–298, June 2021, doi: 10.1109/TIV.2020.3023674.

9. M. Nice, S. Elmadani, R. Bhadani, M. Bunting, J. Sprinkle, and D. Work, "CAN coach: vehicular control through human cyber-physical systems", 2020, International Conference on Cyber-Physical Systems, May 2021 pp132–142 https://doi.org/10.1145/3450267.3450541.

10. S.-A. Shanto, G. Gunter, R. Ramadan, B. Seibold, and D. Work, "Challenges of Microsimulation Calibration with Traffic Waves using Aggregate Measurements", Transportation Research Board Annual Meeting 2021.

11. M. Nice and D. Work, "CAN Coach: Continuous CAN-based Feedback to Change Driver Behavior", Transportation Research Board Annual Meeting 2021.

12. N. Kardous, A. Hayat, S. McQuade, X. Gong, S. Truong, P. Arnold, A. Bayen, and B. Piccoli, "A rigorous multi-population multi-lane hybrid traffic model and its mean-field limit for dissipation of waves via autonomous vehicles", Transportation Research Board Annual Meeting 2021.

13. E. Vinitsky, Y. Du, K. Parvate, K. Jang, P. Abbeel, and A. Bayen, "Robust reinforcement learning using adversarial populations", https://arxiv.org/abs/2008.01825.

14. F.-C. Chou, M. Gibson, R. Bhadani, A. Bayen, and J. Sprinkle, "Reachability Analysis for FollowerStopper: Safety Analysis and Experimental Results", 2021 IEEE International Conference on Robotics and Automation (ICRA); pp. 8607–8613, https://doi.org/10.1109/ICRA48506.2021.9561360.

15. D. Gloudemans and D.B. Work, "Fast Vehicle Turning-Movement Counting using Localization-based Tracking," 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) 2021.

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3. C. Wu, E. Vinitsky, A. Kreidieh and A. Bayen, Multi-lane reduction: A stochastic single-lane model for lane changing, 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), 2017, pp. 1–8, doi: 10.1109/ITSC.2017.8317733.

4. B.S. Kerner, Physics of autonomous driving based on three-phase traffic theory, arXiv preprint arXiv:1710.10852, 2017.

5. This is a simplification, cf. PPO for more details

Acknowledgements

The project PIs would like to thank Senior Engineering Manager and Project Coordinator, Dr. Jonathan Lee, for his leadership and effort in assembling this report.

CIRCLES would like to thank Dave Anderson and Brett Aristegui for their technical and project support.

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Finally, the team wishes to thank all the campus administrators—Peter Gudlewski, Jason Holmes, Kristy Kruse, Jack Long, Sara Maddox, Paul Martinez, Camie Morrison, Laman Sadaghiani, Dannielle Sesay, Missy Sheehy, Wendy Turner, Hera Walker, Elysa Weiss—for everything that they do behind the scenes.

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: December 31, 2023
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. Using existing technology, we aim to demonstrate significant gains without the need for 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. A key feature of our approach is its 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. The focus will be on enabling vehicle-to-infrastructure (V2I) applications even at low connected vehicle penetration levels.

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 and advanced vehicle dynamics models.

Objective 3: Validate ability to reduce corridor fuel consumption by an average of 20% using controlled experiments at ORNL and real-world testing in the connected infrastructure and vehicle testbed 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 C-V2N) 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 will be built on enhanced infrastructure- and vehicle-based sensing and connectivity capabilities. 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. A key feature of our approach is its 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 proposed sensor fusion methodologies, signal optimization strategies and vehicle connectivity has the potential to result in an estimated energy reduction of 20%.

After considering major anticipated events (road construction, seasonal changes, detour routes, etc.) around the Tuscaloosa deployment region we identified the final corridor and have recently completed installation of the detection and communication hardware in collaboration with AL 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 Rd. serves significant industry located around the airport and utilizes eastbound McFarland Blvd (US82) to access I20/59. 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 Blvd. Figure II.1.7.1 shows images of the hardware deployed on a roadside signal pole as well as the camera view and radar feeds.

Based on this corridor and the known detection hardware to be deployed, the team-built traffic models, vehicle models, vehicle image detection and radar return sensor fusion methods, and finally collected data from radio communications hardware. All this data will be input into the traffic simulation models and used to develop the optimization routines and ultimately demonstrated the 20% system wide fuel consumption reduction in real-world testing.

If continued, subsequent project periods will first demonstrate via simulation the potential fuel consumption reductions that can be achieved by optimization of traffic signal (V2I) and vehicle trajectories (I2V) operations based upon infrastructure and connected vehicle sensing. Finally, the team will obtain high quality validation data from both the Hardware-in-the-Loop (HIL) testing and real-world testing. The scalability of the methods developed in terms of both effectiveness and costs will be evaluated.

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.

Results

The primary results in project year include traffic model development, connectivity testing and evaluation, sensor fusion development, and probe vehicle instrumentation. The following section includes subset of results including major accomplishments:

- Infrastructure hardware field deployment was completed to serve as the primary data source for sensor fusion in real-world demonstrations.
- Lab-scale sensor fusion is prepared and showing results that give confidence in likely success of the real-world effort in the next stage.
- Demonstrated the functionality of traffic models incorporating advanced vehicle dynamics models based on ≤10% error from probe vehicle test drive trajectories.
- Tested DSRC/C-V2X radio units in a variety of conditions including line-of-sight (LOS), non-LOS, vehicle shadowing impact, and interference due to Wi-Fi signals.

<u>Hardware deployment:</u> As shown in Figure II.1.7.1, the hardware is deployed and operational. This includes camera and radar installations at three intersections in the Tuscaloosa area. The corridor was chosen in coordination with state DOT officials and the project team. Additionally, both DSRC and C-V2X road-side unit (RSU) radios were installed at each intersection to provide vehicle-to-infrastructure connectivity. These systems are all functioning and only remain to be integrated with regional traffic management center for remote access to data feeds.

<u>Sensor Fusion:</u> The primary hardware deployment included camera and radar systems for simultaneous detection of vehicles approaching the intersections. It is critical to effectively merge (fusion) these two data sources and make the best estimate for vehicle locations and trajectories. The methodology for sensor fusion is shown in Figure II.1.7.2. The radar units include a software API for communicating and extracting vehicle locations and trajectories directly. The camera feeds however must be processed by a neural network-based algorithm called YOLO which tracks vehicles including persistent ID numbers, position, velocity, and classification as also shown in Figure II.1.7.2.

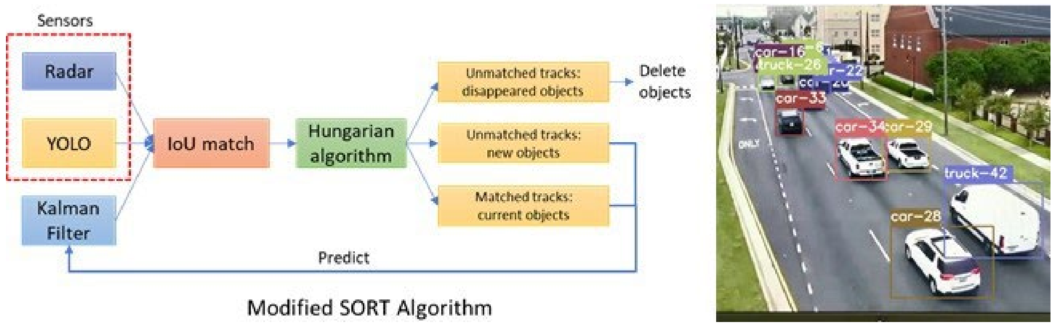

Figure II.1.7.2 (left) Sensor fusion methodology for combining radar and camera based detection at each intersection, and (right) camera based vehicle detection algorithm running on specific image processing hardware that will be located in road-side traffic cabinet to process the raw camera feeds.

The team is working with radar hardware to integrate the software API and consolidate the radar and camera trajectory information into the sensor fusion algorithm. We expect this process to be completed in the coming month and as most of the components have been tested independently with success the team does not anticipate any issues achieving high accuracy in field testing of these hardware and methods.

<u>Traffic and Vehicle Model Development:</u> The traffic corridor under study was modeled in the SUMO (Simulation of Urban Mobility) software package and validated against real-world detector logs for each intersection. The logs include every detector call and signal status change. These logs allowed our team to generate traffic volume and routing inputs for the simulation to capture. Figure II.1.7.3 shows the traffic simulation sections including the three signals and demonstrates the calibration procedure and validation results.

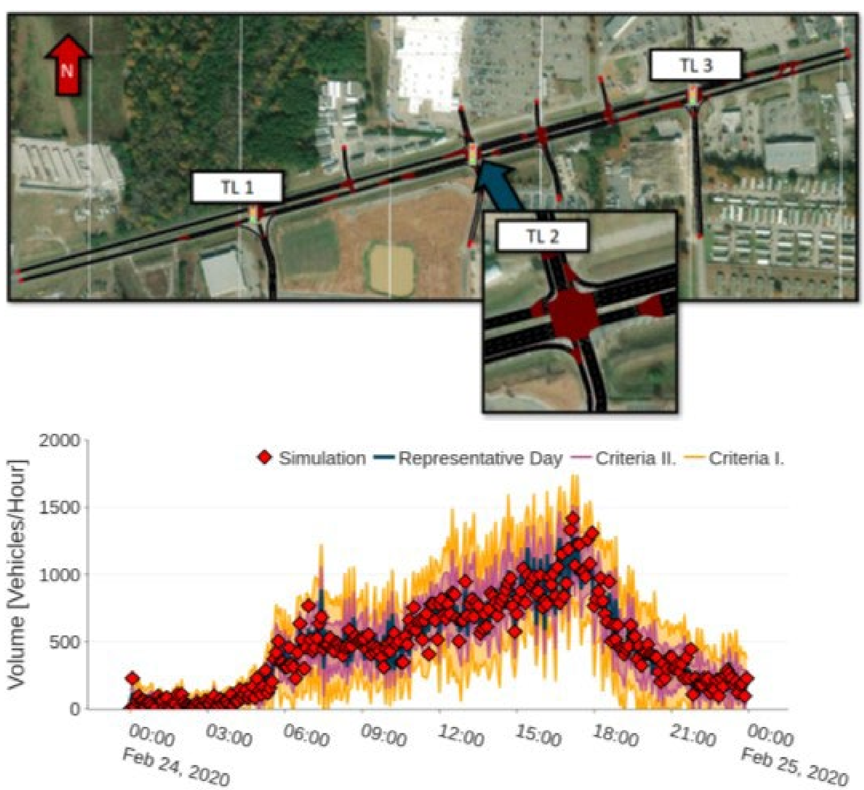

Figure II.1.7.3 (top) Traffic simulation network of deployment corridor overlaid on aerial images, and (bottom) sample calibration results of network per USDOT calibration procedures for microsimulation modeling.

The traffic model validation demonstrates that the total number of vehicles in the network is captured dynamically throughout the day at each intersection and from each approach. To make accurate predictions of energy/fuel consumption more complex vehicle models must be included within the SUMO simulation. This includes a variety of vehicle classifications such as sedan, SUV, and Class 8 trucks. Figure II.1.7.4 demonstrates the importance of this effort as a real-world speed profile is simulated using the default vehicle model and compared to actual measurements. The difference in predicted and actual cumulative fuel consumption is more than 30% (underprediction in this case). A calibrated model (developed in this project) can show much better agreement as shown in Figure II.1.7.5 where the cumulative fuel consumptions agree to better than 1%—far exceeding the Go/No-Go target of 10%.

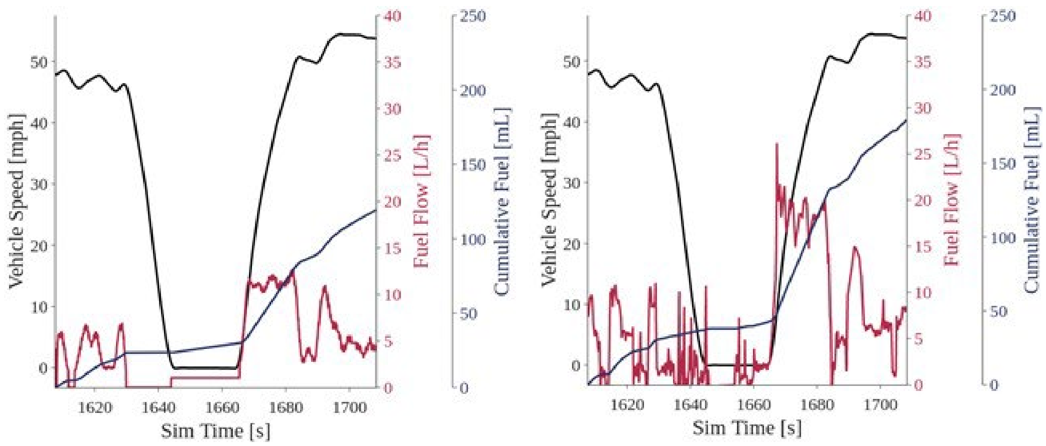

Figure II.1.7.4 Real-world vehicle speed profiles (black) and the respective fuel consumption comparing the simulation prediction using default vehicle type (left) and the actual measured results (right).

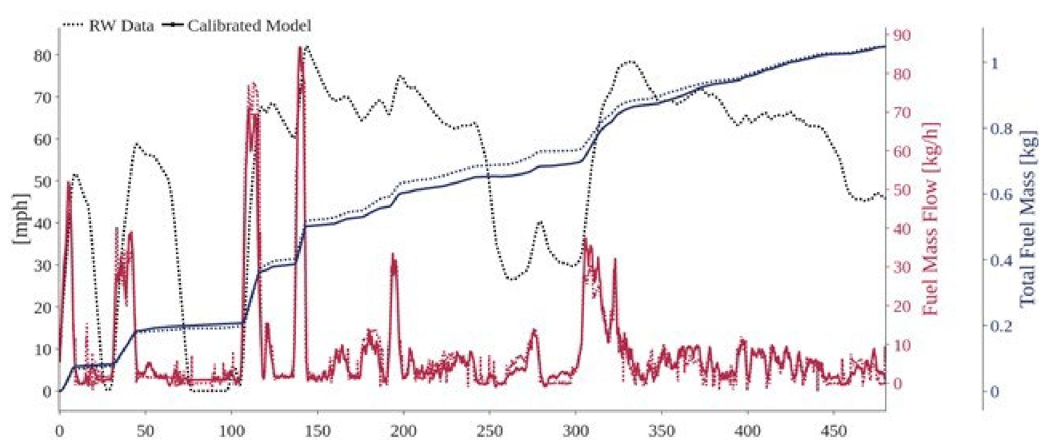

Figure II.1.7.5 Real-world vehicle speed profile (black dash) and predicted instantaneous and cumulative fuel consumption (red and blue) for both measured (dashed) and a calibrated model (solid).

Connectivity Hardware Testing: Several tests were performed examining the abilities of C-V2X and DSRC in different scenarios. Initially, preliminary tests were performed looking at how the C-V2X and DSRC radios perform in an ideal testing environment being connected via a coax cable. Then, static testing was performed to examine the capable bandwidth of the system under different packet sizes and data transmission rates. Dynamic tests with a moving vehicle were performed to examine the capabilities of the system in line-of-sight (LOS) testing and non-line-of-sight (NLOS) testing conditions in a continuous testing environment with the aid of Cohda Wireless' SDK (Software Development Kit). These lab-scale and real-world testing are suitable for guiding both traffic simulation updates and future real-world DSRC/C-V2X testing in the project test corridor.

In C-V2X applications, testing has been done using the Cohda Wireless MK6c evaluation kit. In DSRC applications, testing was done using the MK5 evaluation kit. As an example of testing results, Figure II.1.7.6 shows packet error rates as function of distance as vehicle travels away from RSU which is placed in various obstructed (Positions #1-6) and non-obstructed LOS positions. In this case the transmitter and receiver are the same model while the actual hardware to be installed roadside is a dedicated road-side unit form factor. Other performance metrics such as latency, and bandwidth were also tested and will provide input to traffic simulations for including realistic delays and range limitations of connected vehicles in developing optimization techniques.

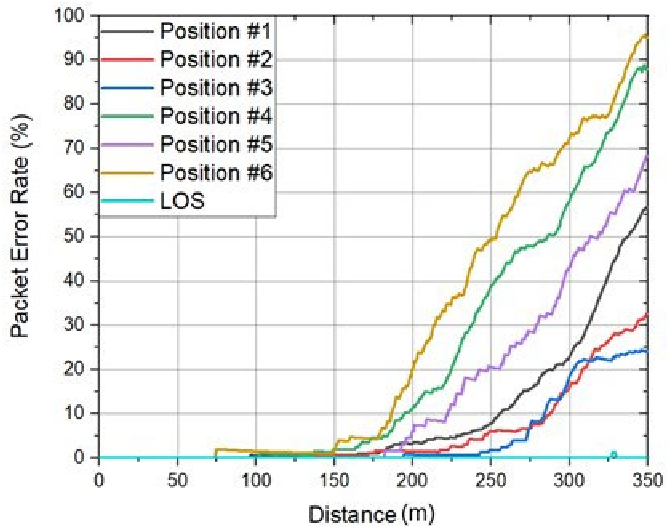

Figure II.1.7.6 Dynamic testing of C-V2X unit in non-LOS and LOS conditions as vehicle traveled away from RSU. Results show strong effect of obstruction (position 1-6) on data loss as indicated by packet error rates.

Conclusions

The project is on-track with objectives and milestones and has everything in place to demonstrate real-world vehicle detection and sensor fusion required to obtain holistic view of the traffic in the deployment corridor. Simulation tools to mimic this detection are also in place to begin development of traffic control optimization methods based on this awareness. Close collaborations with state DOT officials and the clear potential for dramatically impacting system wide fuel economy in near term using these approaches represents an exciting opportunity. 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.

Acknowledgements

The team would like to acknowledge the following Co-Principal Investigators at the University of Alabama: Professor Bharat Balasubramanian, Professor Alex Hainen, Professor Nathan Jeong, and Professor Hwan-Sik Yoon. The team would also like to thank Danielle Chou for her interest and input in the first year of this project as an AAAS S&T Policy Fellow supporting the technology management of the project.

II.1.8 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: December 31, 2023
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, Valence, National Renewable Energy Laboratory (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 (V2C) 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 100-truck field test with a commercial fleet partner.

Fiscal Year 2021 Objectives:

- 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 100-truck field test during 2022 and 2023
- Implement a proof-of-concept (POC) 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 (TRL) process to evaluate the new technologies for production and commercialization. A representative program overview can be seen in Figure II.1.8.2.

While telematics development is a 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 (COTS) 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 Intelligent Driver Assistance System (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 Route-E tool and Esri's ArcGIS software. The route may not be the shortest time or distance but will be the most energy efficient. 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 (FMS) 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.

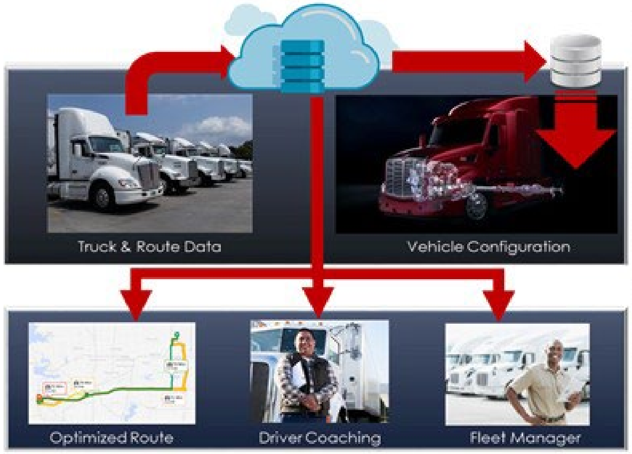

Figure II.1.8.1 Overview of CoVaR data flow

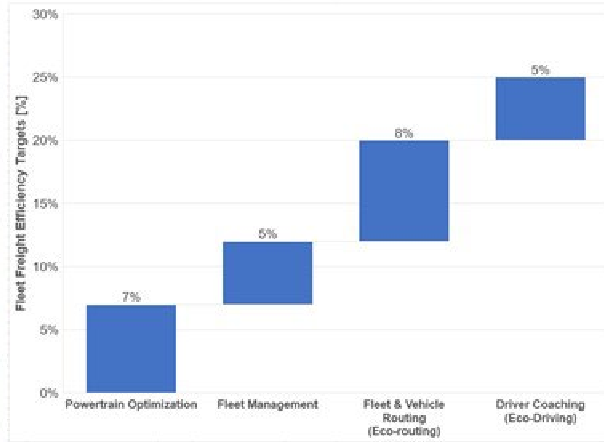

Figure II.1.8.2 Waterfall graph of energy efficiency targets

Results

The major focus of the first year of the Co-Optimization of Vehicles and Routes program has been on the technology development side. Each of the technologies mentioned previously have gone from initial concepts through design phases and early prototypes. One major milestone of the technology development phase is a proof-of-concept demonstration truck being operated at the PACCAR Technical Center. Below is a summary of each technology's development throughout the first year of the program.

Telematics & Cloud Infrastructure

Several commercial off the shelf (COTS) 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. During the first year of the program, the team was able to create a working prototype of this solution, with data being collected, processed, and sent to the cloud from a truck driving on public roads.

The cloud infrastructure for the program has been developed and stood up in Microsoft Azure by Esri. An overview of the cloud infrastructure can be seen in Figure II.1.8.3.

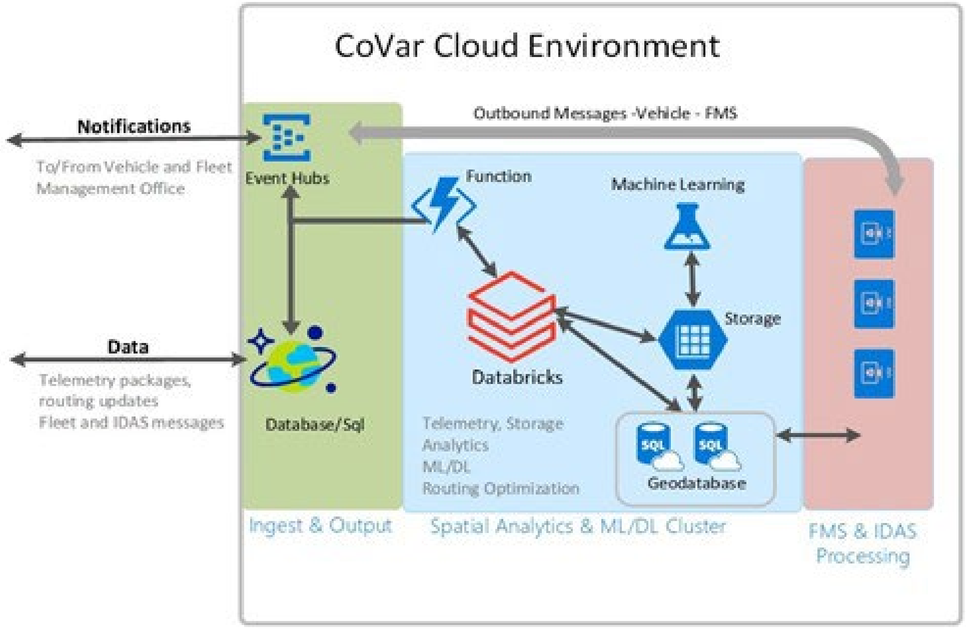

Figure II.1.8.3 CoVaR cloud architecture developed by Esri

The cloud infrastructure is currently stood up and operational, with the ability to receive real-time data from the demonstrator truck. Work will continue on the Extract, Transform, and Load (ETL) functionality as well as on Databricks.

Eco-Routing

The Eco-Routing portion of the program has made significant progress in the first year. NREL's Route-E powertrain tool has been trained on real-world PACCAR vehicle data to accurately predict the energy consumption of a possible route. This service will be utilized to provide the most energy efficient route. It may not be the shortest distance or time but will consume the least energy amongst the possible routes. This service will be integrated with Esri's ArcGIS tool to provide turn-by-turn directions on the in-cab display. This integration work is ongoing and will be a major focus of the remainder of 2021. An example of the eco-routing function using Route-E can be seen below in Figure II.1.8.4.

Figure II.1.8.4 Example of eco-routing used in CoVaR

Eco-Driving

The Eco-Driving portion of the program 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. 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. This will also include historical data of the same route that was previously driven in the fleet as a comparison for how the driver did.

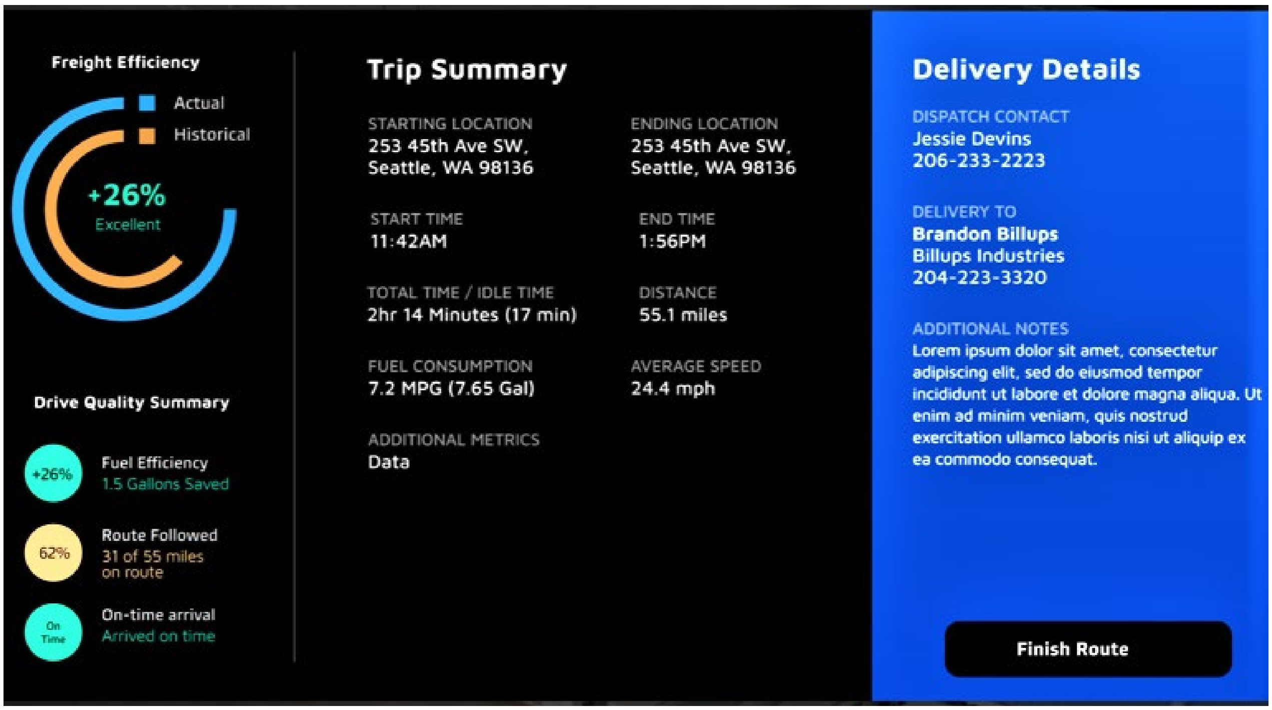

Figure II.1.8.5 Example of possible post-trip driver coaching metrics

Fleet Management Dashboard

The framework for the fleet management dashboard has been developed during the first year of the program. The team has worked to define requirements and key metrics for the dashboard. The dashboard will be a real-time cloud-based service to provide a fleet manager with performance and operation metrics of their fleet. This will help reduce deadheading and gain fleet freight efficiency by monitoring the performance of the fleet. This also may help with finding early performance issues amongst vehicles within the fleet. As we coordinate with a fleet partner, we will work to integrate with their current specific use case and tailor the fleet management dashboard to their fleet.

Figure II.1.8.6 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 inputted from the user. The tool can optimize and provide a trade-off relationship for energy efficiency, engine performance, selling cost, and more. The tool is only operational for diesel vehicles currently but will add BEVs in the coming year. The team has developed a working prototype application in MATLAB and is continuing to train the machine learning models to improve accuracy of the results.

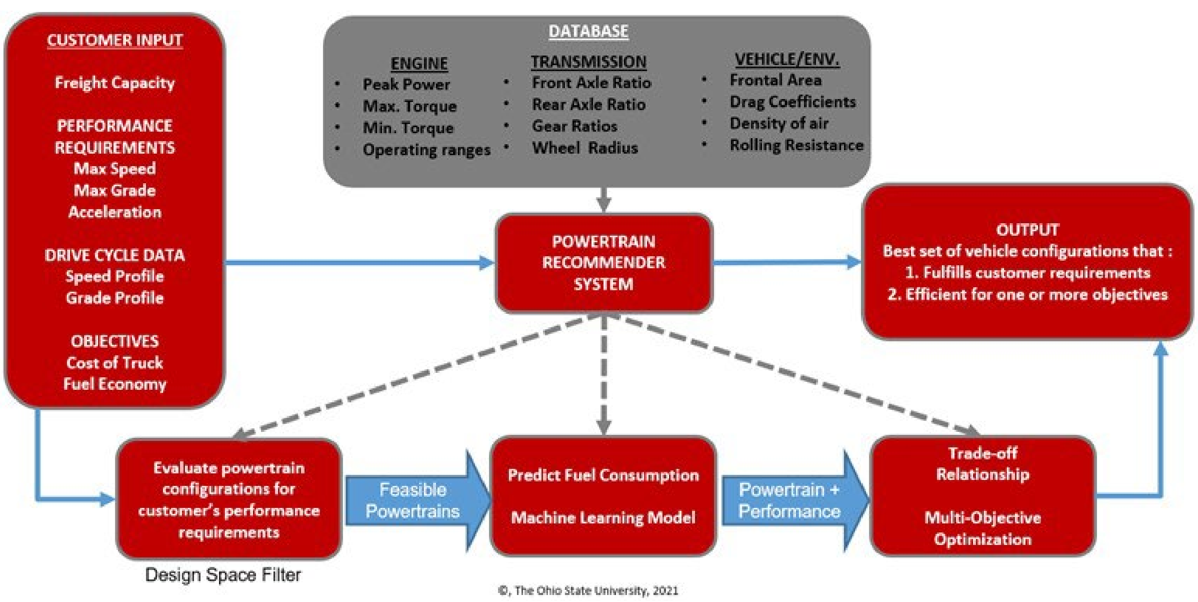

Figure II.1.8.7 Framework for the powertrain recommender system

Conclusions

Over the first year of the program, 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. The team also developed a working prototype of the powertrain recommender system tool. Over the next two years, the team will work to onboard a fleet partner and field test the CoVaR technologies on 100 trucks. The team will also work to assess the potential and real-world impact of these technologies on freight efficiency improvements, with an overall goal of improving by 25%.

Key Publications

1. DOE Quarterly Progress Report Q1 – January 30th, 2021
2. DOE Quarterly Progress Report Q2 – April 30th, 2021
3. 2021 Annual Merit Review Presentation – June 24th, 2021
4. DOE Quarterly Progress Report Q3 – July 30th, 2021
5. DOE Quarterly Progress Report Q4 – October 30th, 2021.

Acknowledgements

Kimberly Nuhfer, Project Manager DOE.

II.1.9 Connected and Learning Based Optimal Freight Management for Efficiency (Cummins)

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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, Argonne National Laboratory, University of California Berkeley, and Michelin North America will 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 freight management system that is used to demonstrate freight operation system efficiency improvement of 20%, or more, over a baseline fleet system that covers multi transportation modes including long-haul, short-haul and less-than-truckload (LTL), and/or pick-up and delivery (P&D).

Approach

The objective of the project will be achieved by development and validation of the proposed technology in three phases:

- **Phase 1 – Technology Development (2021):** A freight system simulation will be 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 will be characterized, and the baseline freight operation will be verified in simulation. The path to target will be refined for optimal freight operational efficiency.
- **Phase 2 – Technology Implementation and Demonstration in Simulation (2022):** The learning and optimization algorithms will be integrated with the POLARIS freight simulation models and the baseline fleet operation. The freight operation scenarios will be defined. A ≥20% freight operation efficiency will be demonstrated in simulation and the specifics conditions where this improvement is possible will be detailed. The significance or impact on fuel savings of the various levers will be 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 will be refined with different levels of technology penetration.
- **Phase 3 – Technology Validation on Fleet (2023):** Evaluation with fleet data will be completed. The utilization and refinement of algorithms and digital models, and the energy and CO_2 savings validation on fleet will be 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

As shown in Figure II.1.9.1, a system of systems simulation platform to model the operation of the baseline fleet is developed and validated using fleet operation data. This platform can model the impact of HDMD advanced powertrain vehicle technologies, connectivity, and automation. The model is used to develop the learning and optimization fleet operation efficiency algorithms and demonstrate the path to target under different scenarios.

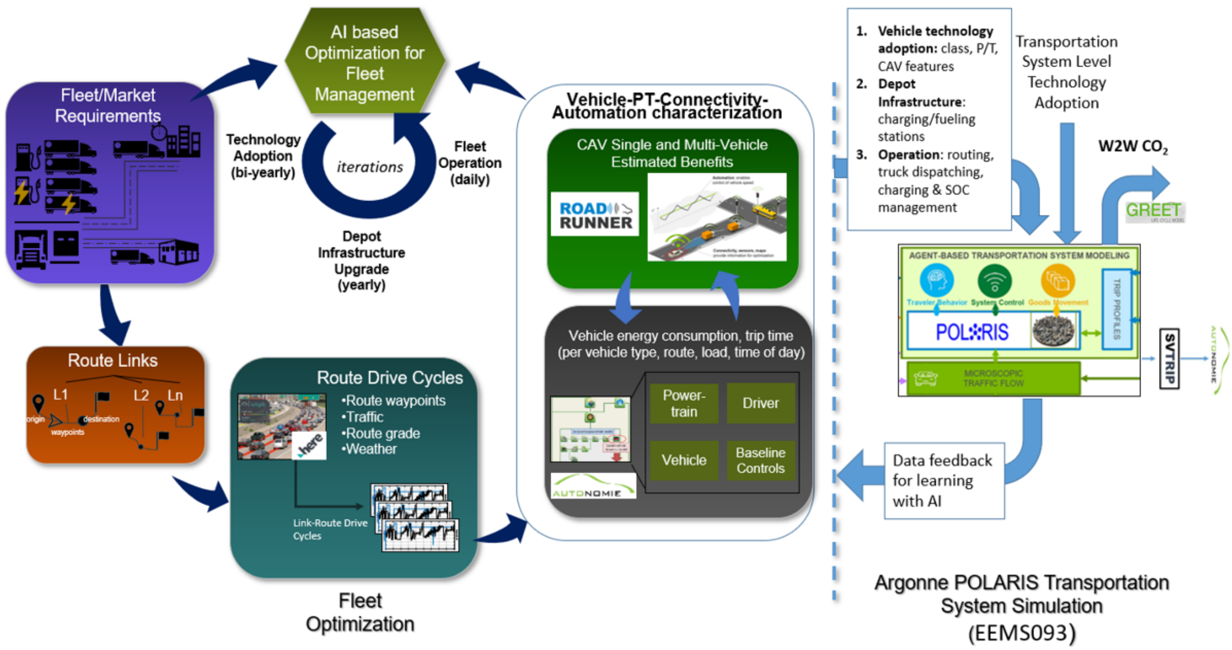

Figure II.1.9.1 System of System Simulation for Freight Operation

Developing the POLARIS freight system simulation

The fleet operation requirements and network defined through collaboration with Venture fleet are used to model baseline fleet operations. The baseline fleet requirements including the operation network in U.S., load demand, stop and delivery locations and schedules are defined by analyzing telematics data and logistics requirements. Six major fleet operations including 5 dedicated divisions in different U.S. areas and one over the road (OTR) division are selected to be modeled in this project. Venture provided a total of 90 days of fleet operations for their fleets. Baseline fleet operations will involve simulating all 90 days of fleet operations for six selected Venture divisions in the Workflow.

The six selected Venture divisions (Figure II.1.9.2) are a mix of regional and OTR (over the road) operations that covers most of the US, including the greater Midwest and California, which were previously not included in POLARIS use cases. To model baseline fleet operations, Argonne team developed a new national POLARIS model. This allows the team to simulate fleet operations everywhere that Venture operates. The baseline network is based on the Federal Highway Administration Freight Analysis Framework network. The network was enhanced with additional data to improve energy estimation in the workflow. Road grade data from the US Geological Survey Digital Elevation Model are added to POLARIS as it is an important factor for medium/heavy trucks energy consumption. Argonne added data from the National Bridge Inventory and National Tunnel Inventory to include as explanatory variables in the energy consumption analysis.

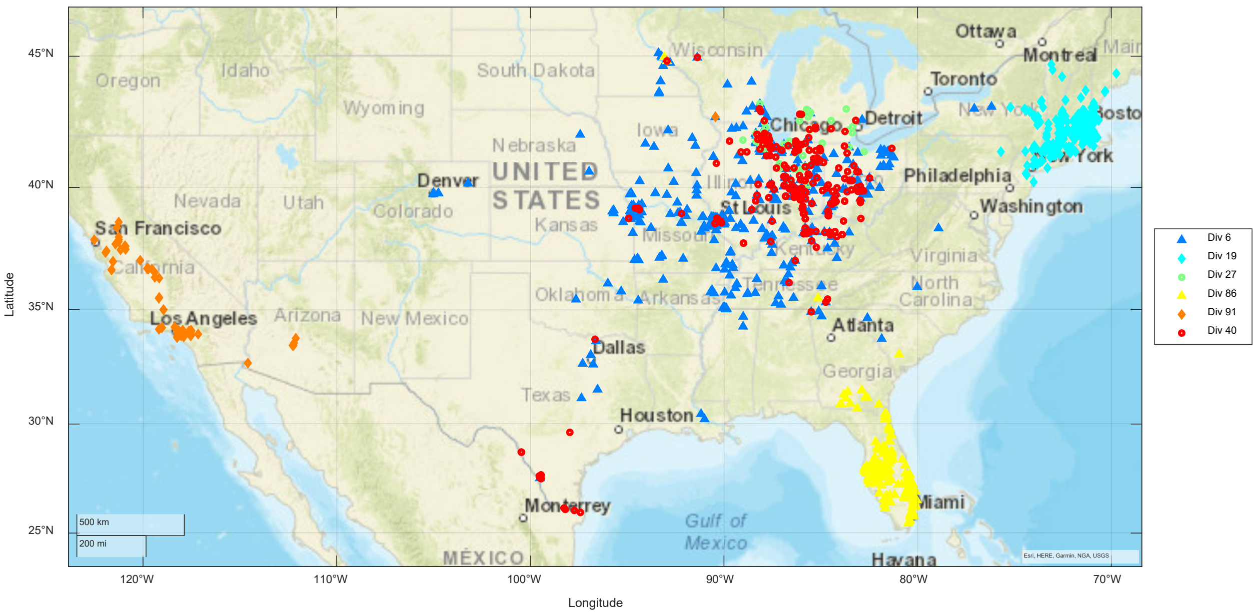

Figure II.1.9.2. Venture Fleet Operation Locations for Selected Divisions (Sample Data from [Venture Fleet](#))

AMBER/Autonomie Updates

Argonne provided Cummins with Autonomie models for Class 6 delivery, Class 8 regional and long-haul trucks. Models for conventional, hybrid, plugin hybrid, electric as well as fuel cell powered vehicles were provided. The models include 10 vehicle models for long-haul and regional haul class 8 trucks with Diesel, Mild Hybrid, Extended Range Electric, Fuel Cell, and Fully Electric powertrains and 3 vehicle models for class 6 P&D with Diesel, Extended Range Electric and Fully Electric powertrains. The models were sized and calibrated by Cummins (Figure II.1.9.3) to represent the baseline vehicle models for the corresponding long-haul, regional haul and P&D operations. These vehicle models will be used to assess the impact of new powertrain technology adoption, connectivity and automation, and overall fleet operation optimization. Argonne also made several improvements to AMBER/Autonomie (Figure II.1.9.4) to increase simulation speed, protect proprietary data during the simulation, and calibrate the controllers for vehicle features in this study. This supports the implementation of larger design of experiment and optimization in the study.

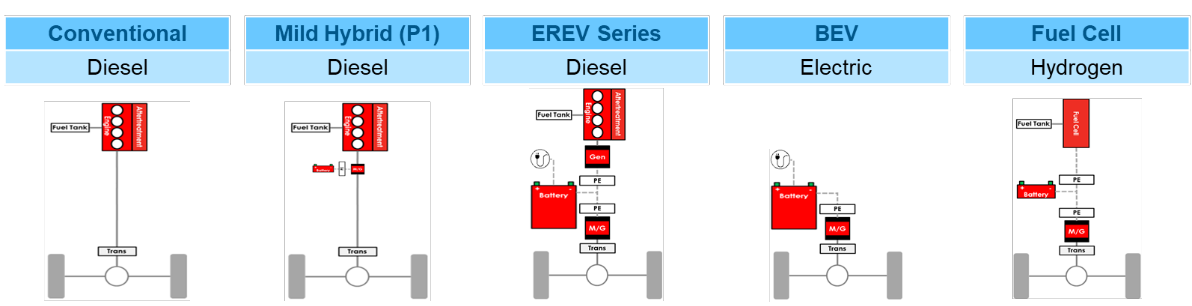

Figure II.1.9.3. Powertrain Architectures Under Study

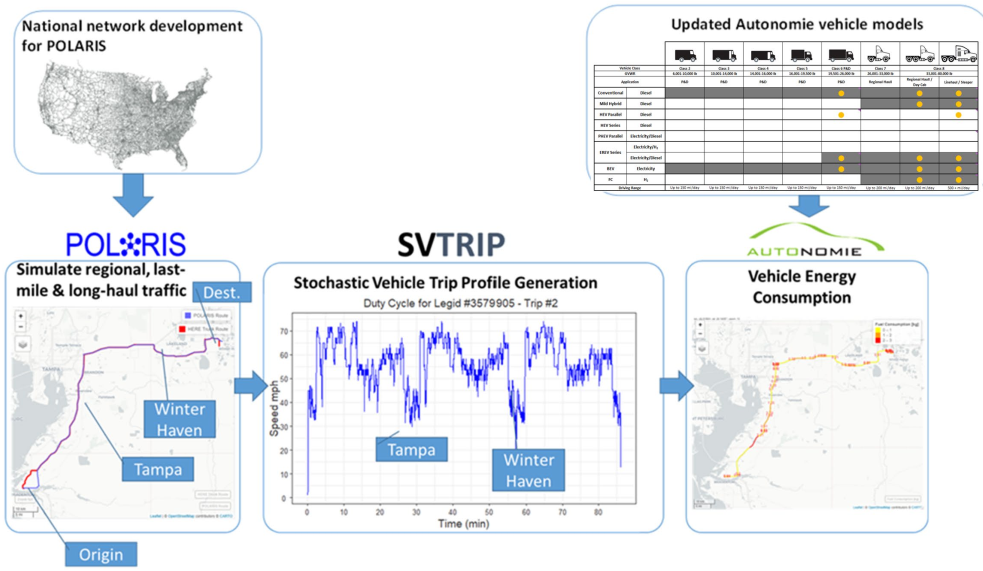

Figure II.1.9.4 Updated Workflow for baseline freight simulation

Verify Baseline Freight Operation in Simulation (ongoing)

The transportation fleet characteristics are integrated into the freight system simulation framework for all six fleets to model baseline operation. This will serve as a reference for future tasks for the freight efficiency and properties of the baseline. In FY2021, the baseline freight system simulation in POLARIS is developed for one of the Venture fleets. Argonne is now updating the simulation to include all six of the selected Venture fleets and will verify operations with distance and fuel efficiency.

Connectivity and automation vehicle (CAV) characterization (ongoing)

To assess the benefits of CAV features (advanced eco-driving with L4 automation and platooning), a representative route for class 8 heavy duty truck in Indiana is selected for simulations. This representative route is from a study done in an ongoing Cummins-DOE joint project (DE-EE0008469) to represent road grade and traffic conditions for this application [3]. As shown in Figure II.1.9.5, the route begins and ends in Columbus, Indiana at Cummins Machine Integration Center (CMIC) with a halfway/turnaround point in Evansville, Indiana. The round-trip length is 329 miles and consists of sections from I-65, I-265 and I-64, all within the state of Indiana. There is a mix of low, medium, and high-grade sections. The results indicated the optimal trade-off between fuel economy and trip time and additional energy saving and GHG CO_2 reduction comparing to the baseline. The CAV models will be integrated into the fleet optimization and simulation platform to assess the impact of this technology toward the project objectives.

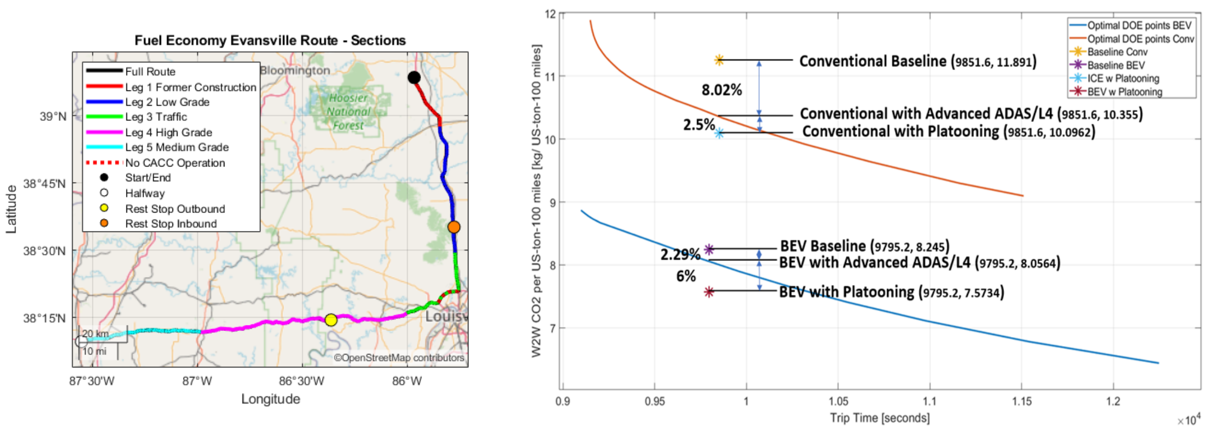

Figure II.1.9.5 CAV Characterization for Regional Haul Trucks (Conventional V.S. Electric)

Learning and Optimization Algorithms for Optimal Fleet Operation (ongoing)

An overall approach for Learning and Optimization of Fleet Operation is shown in Figure II.1.9.6. This is being developed through collaboration with the University of California, Berkeley. Specifically, we focus on a poorly understood issue in fleet operations which becomes critical for low-emissions transportation, and especially electrified trucks. The issue is uncertain energy consumption along routes, due to varying payload weights, traffic conditions, weather conditions, etc. We plan to generate hundreds to thousands of sample energy consumption calculations to statistically characterize the uncertainty. However, generating this many samples with Amber/Autonomie is untenable. Consequently, we have trained machine learning models to predict energy consumption, as a surrogate model, given important features.

Next, an optimization model that determines the vehicle's route, vehicle type, charging schedule, state (bobtail, empty trailer, full trailer) and more is formulated to minimize energy. This falls within the classic vehicle routing problem category, for energy. The key novelty, however, is incorporating uncertainty, most notably at random "edge costs" in the network graph. Our planned approach is to apply 'distribution robust' optimization. It works as follows. From energy consumption gathered to-date, one can assemble an empirical distribution of energy consumption along each edge. This data, however, might be limited so the empirical distribution and may not accurately represent the true distribution. Consequently, one can optimize with respect to the empirical distribution, yet hedge against additional uncertainty because of the difference between the empirical and true distribution. The "learning" part refers to updating the empirical distribution as new data is gathered, and then reducing the hedging between the true and empirical distribution, since they will converge as you gather more data. This optimization technology on 'distribution robust' optimization is a recent advancement in operations research and management science. This project will be the first attempt, to our knowledge, that applies this technology to reducing energy and emissions in freight operations. Importantly, the results will be critical to achieving the efficiency improvement target in logistics operation, while ensuring reliable high-performance operation.

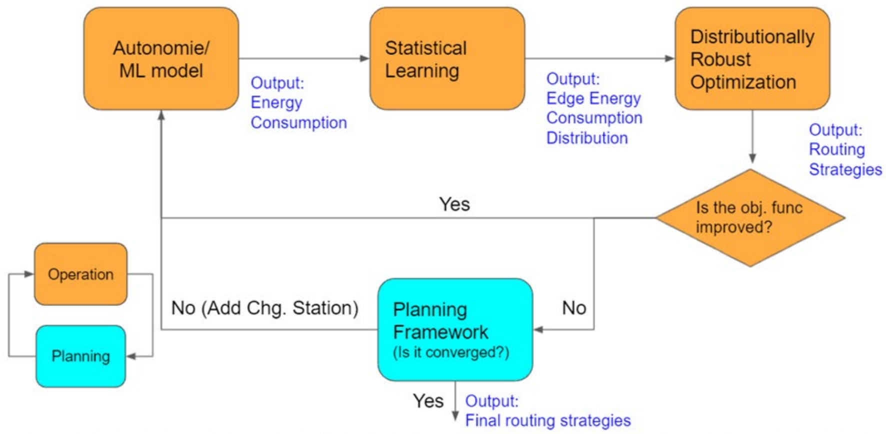

Figure II.1.9.6 The schematics of proposed Learning and Optimization for Fleet Operation

Conclusions

Emerging technologies from advanced powertrain systems such as hybrid electric, fuel cell, and fully electric along with connectivity and automated vehicle solutions are being developed for decarbonization of on road freight transportation system. 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, would reduce the effectiveness of these advanced technologies to improve the freight operation efficiency. In this project, novel AI and first principle models along with learning and optimization algorithms are being developed to improve freight operation efficiency by more than 20%. These models have been developed and are validated with fleet operation data. The developed models and algorithm will be integrated in the Phase 2 of the project in 2022 to demonstrate more than 20% freight operation efficiency improvement.

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3. Borhan, H., Lammert, M., Kelly, K., Zhang, C. et al., “Advancing Platooning with ADAS Control Integration and Assessment Test Results,” *SAE Int. J. Adv. & Current Practice in Mobility* 3(4):1969–1975, 2021

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II.1.10 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: December 31, 2023
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 transportation network companies (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, 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 of 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 to improve the energy efficiency of the transportation system. The team will conduct validations in both simulations using POLARIS and experiments in real vehicles using a novel human-and-vehicle-in-the-loop pooled rideshare (HVIL-PR) platform in which a pooled rideshare transportation system will be simulated in POLARIS and some simulated PR vehicles will be replaced by real PR vehicles.

Objectives

The overall goal of the project is to increase the pooled rideshare user acceptance to help increase the efficiency of the transportation system. 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 simulation and experimental validations of the pooled rideshare models and technologies

Approach

Survey-based Human Factors Study in Pooled Rideshare

The survey-based human factors study aims to collect comprehensive human factor data on pooled rideshare based on research studies. This will generate holistic human factors data on pooled rideshare and provide foundational knowledge of the factors which can affect people's acceptance on pooled rideshare. The team utilized the findings from existing research work, merged the goals of this DOE project and took into consideration the impact of COVID-19 on travel behaviors to develop the survey. The team has completed a comprehensive literature review regarding rideshare including pooled rideshare. By summarizing the existing work, a new mind map was created to develop key factors for our survey-based human factor study on pooled rideshare. The summary of our survey to key factors is shown in Figure II.1.10.1.

Based on the factors, the team has designed the survey questions by iteratively discussing every single question based on the abundant experiences of all partners including Clemson, J.D. Power, Argonne National Lab and Ford to ensure that the questions can result in the trustable responses from various audience. The structure of the survey is shown in the Figure 1. The survey aims to explore the users' current travel behaviors and reasons for their choices and ultimately explore factors affecting their receptiveness to utilizing pooled rideshare. The survey focuses on the human factors-centered reasons for acceptance and the barriers to adoption which will feed next phase of the project. The survey consists of seven sections. After ensuring potential participants are 18 years of age or older and obtaining consent, a baseline of their experience using rideshare service is followed by questions to assess their transportation needs. This section explores their needs as well as their experience with various transportation services, including personal and pooled ridesharing. Then, participants report their willingness to consider utilizing a pooled rideshare. Based on their answers, participants determine what factors influence their decisions to utilize or not utilize pooled ridesharing. This will help us to understand why individuals do or do not consider pooled ridesharing. Then questions about optimizing one's experience are completed to provide insight as to which factors will influence decisions to utilize pooled ridesharing in the future. The final section is on demographics. Originally, individuals who are rideshare drivers also had an additional section, which was later removed after pilot studies due to long time of survey fatigue.

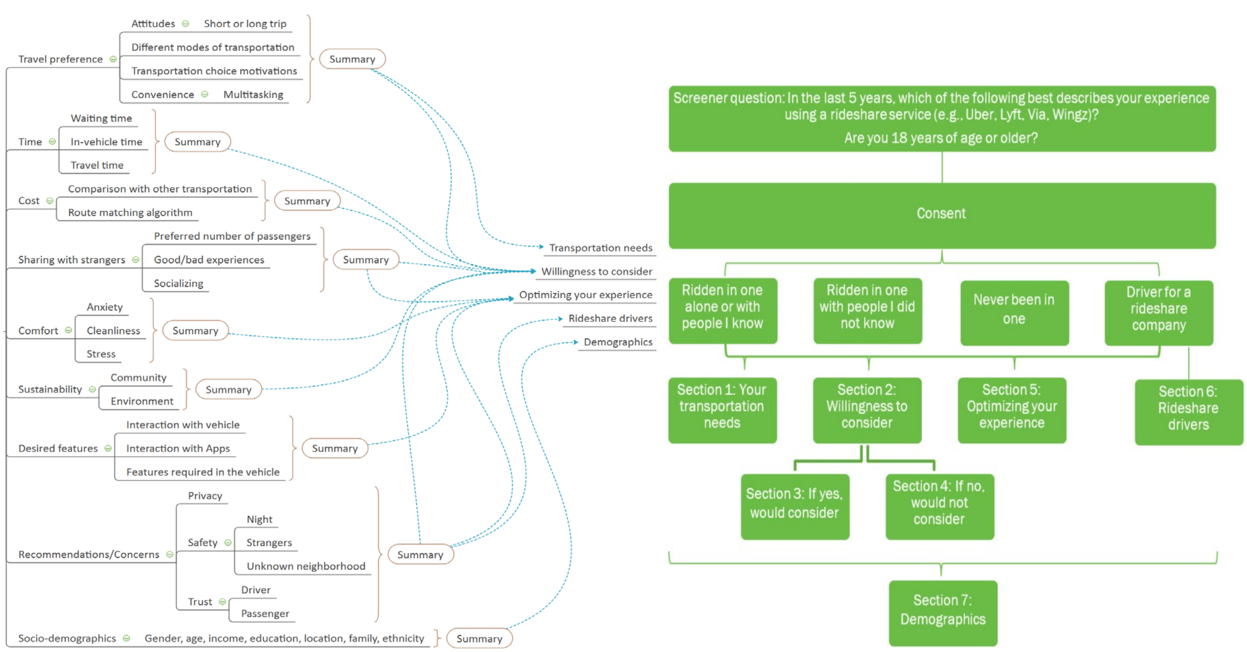

Figure II.1.10.1 Summary of existing research factors and structure of the survey on pooled rideshare

The team finalized the survey on June 4th and from that day on focused exclusively on programming. Qualtrics was used in the upstate of South Carolina while J.D. Power used a proprietary system. Recruitment started on July 12th when the survey was deployed and ended on August 11th. The Clemson team used all means for the recruitment of participants for the survey including radio advertisements, TV stories on News Channel 4 and News Channel 7, social media, and thousands of survey flyers distributed throughout locations in the Upstate of South Carolina.

In-situ Human Factors Study in Pooled Rideshare

The next task is to collect detailed human factors data on pooled rideshare and provide the team with more concrete information to perform subsequent human factors analyses and modeling of pooled rideshare acceptance. The study will be based on the key factors discovered from the survey-based study results to create in-situ scenarios to investigate how these key factors affect the user acceptance of pooled rideshare. The situations and contextual settings with the low acceptance of pooled rideshare will be the primary focus of this task. The scenarios will be designs of different pooled rideshare experiences related to the key factors for different groups of people. We originally proposed to record such scenarios in pooled rideshare vehicles and render these scenarios to participants through either screens or virtual reality headsets. We will then collect data on how different factors will affect the user acceptance of pooled rideshare for different groups of people.

Simulation Validation of Pooled Rideshare in POLARIS

The task is to develop a simulation of pooled rideshare service to validate the designed pooled rideshare technologies in the future as well as evaluating the improvement of energy savings of the design technologies on the transportation system. We will use the POLARIS as the basis of the simulation and incorporate pooled rideshare modules into it in collaboration with Argonne National Lab. We will create interfaces to incorporate the pooled rideshare acceptance models which are to be developed based on the human factory study results into POLARIS. With this, we will simulate the existing pooled rideshare technologies and use the pooled rideshare acceptance models to accept or decline a pooled rideshare vehicle for a pooled rideshare user. We will then be able to evaluate the performance of these technologies including their impacts on energy savings. Furthermore, we will also simulate the newly designed human factor incorporated pooled rideshare technologies by leveraging the pooled rideshare user acceptance model in POLARIS. A comparison of the new technologies to exiting technologies including their impacts on energy savings will be possible using this simulation of pooled rideshare in POLARIS.

In addition to using existing cities in POLARIS such as Chicago, Bloomington, and Austin, we will also create a new city of Greenville in POLARIS to not only expand the capability of POLARIS but also support future experimental validations with people in Greenville. We will first build the model of Greenville in POLARIS and then incorporate the pooled rideshare modules including the pooled rideshare technologies and user acceptance models into the simulation.

Experimental Validation of Pooled Rideshare Vehicles

The task is to develop real pooled rideshare vehicles to validate the designed pooled rideshare technologies in the future with human participants in Greenville. We propose to construct an innovative human-and-vehicle-in-the-loop pooled rideshare (HVIL-PR) platform in which real human-driven or automated vehicles can interact the simulated traffic in POLARIS. The architecture of the HVIL-PR platform is shown in Figure II.1.10.2. It consists of a POLARIS simulation server, real automated vehicles, real human driven vehicles, a global positioning system, and cellular communication

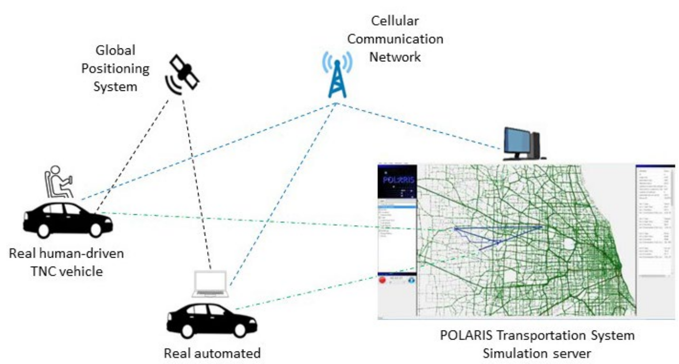

Figure II.1.10.2 Human-and-vehicle-in-the-loop pooled rideshare (HVIL-PR) network. The simulation server will simulate a virtual transportation system in POLARIS. We will replace one or more of the simulated automated vehicles by our real human-driven or automated PR vehicle. The HMI technologies can be implemented in these vehicles and the trips of these vehicles will be derived using various pooled rideshare technologies based on the traffic and scenario in POLARIS. This allows us to create and control a variety of traffics and scenarios related to pooled rideshare and conduct the experimental evaluations with real pooled rideshare vehicles.

Results

Results of survey-based Human Factors Data Collection in Pooled Rideshare

We have deployed the survey and collected data from 5,385 participants who have completed the survey including 2,000 from national wide, about 500 each from six cities including Atlanta, Austin, Chicago, Detroit, New York City and San Francisco, and 384 from Upstate South Carolina. Overall participants have a mean age of 46.5 (SD=17.5), ranging from 18 to 95 years. The overall distribution of age groups is 18–24 (12.9%), 25–34 (17.3%), 35–44 (17.1%), 45–54 (18.7%), 55–64 (15.2%) and 65+ (18.8%). The participant's distribution by generation for each location is shown in Figure II.1.10.3. Of the total 5,385 participants, 52.1% were female, 47.3% were male, and 0.3% preferred to self-describe. There is a broad distribution of age and gender in our sample. The Upstate SC sample has a large proportion of Boomers in comparison to other cities.

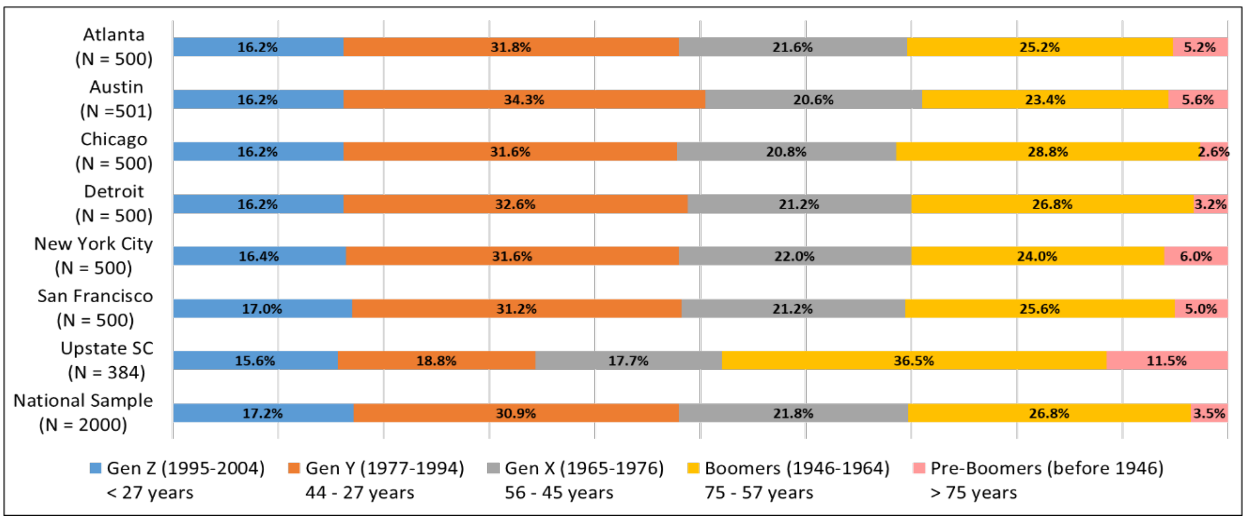

Figure II.1.10.3 Generation distribution of survey participants by city

Results of Preliminary Analysis of Human Factors Barriers in Pooled Rideshare

1) Preliminary Analysis on Rideshare Experience and Willingness to Consider Pooled Rideshare

The most frequently selected response with 51.4% of the sample was "ridden in one alone or with people I know", followed by "never been in one" with 43.3%, then "ridden in one with people I did not know" with 15.6%, and 4.1% indicated being a "driver for a rideshare company". Out of the total sample of 5,385, 41.0% said "yes", 43.7% said "no", and 15.3% responded with "don't know" to willingness of considering pooled rideshare. As shown in Figure II.1.10.4, for those who had rideshare experience, the responses were "definitely will" (10%), "probably will" (47%), "probably not" (19%), "definitely not" (12%) and "don't know" (13%). For those who did not have rideshare experience, the responses were "definitely will" (2%), "probably will"

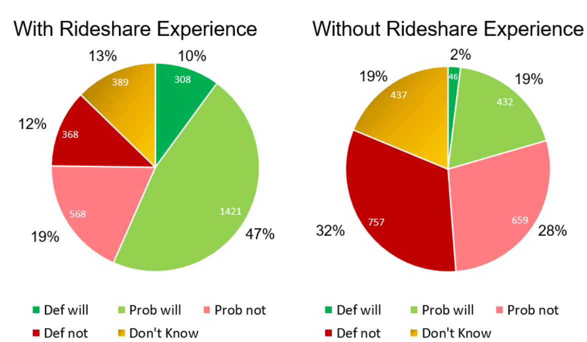

Figure II.1.10.4 Willingness to consider pooled rideshare

(19%), "probably not" (28%), "definitely not" (32%) and "don't know" (19%). These indicate that many people would like to consider pooled rideshare regardless of their experience but only a small population would use existing pooled rideshare.

2) Preliminary Analysis on Most Important Factors to Utilize Pooled Rideshare

The responses to the most important factors in decisions to utilize a pooled rideshare in the future were "personal safety" (35.3%), followed by "travel cost" (19.1%), "convenience" (16.5%), reliable transportation (11.5%) and overall travel time (7.5%). The results are shown in Figure II.1.10.5. To determine the factors relevant in determining willingness to utilize pooled rideshare, participants were shown a list of 25 factors grouped into 6 categories including travel time and cost, environmental, social, personal safety, reliability and accessibility, and convenience. The top factors for participants who would consider pooled rideshare are reliability, personal safety, time, convenience, cost, and environmental factors, while the top factors for participants who would not consider pooled rideshare are personal safety, convenience, privacy, time, reliability, and cost factors. A deeper analysis into these factors is being conducted by the team and will be included in our technical report.

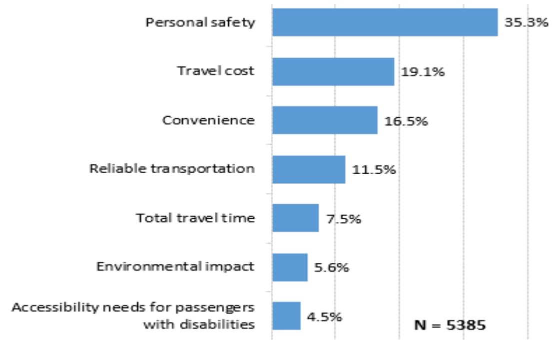

Figure II.1.10.5 Most important factors to utilize PR

3) Preliminary Analysis on Willingness to use Pooled Rideshare after Meeting Discussed Needs

When comparing the willingness of different participants to use or not use pooled rideshare at the beginning of the survey and at the end by assuming a pooled rideshare service meets all of the discussed needs, the responses were "definitely will" (21%), "probably will" (45%), "probably not" (23%), "definitely not" (9%) and "don't know" (2%) for those with rideshare experience, and "definitely will" (6%), "probably will" (28%), "probably not" (31%), "definitely not" (29%) and "don't know" (5%) for those without rideshare experience. The results are shown in Figure II.1.10.6. This indicates that people are more likely to use pooled rideshare if their needs can be met. All the results so far have shown that many people are willing to consider pooled rideshare, but they may have expectations on factors that need to be addressed. Therefore, tour team needs to further explore how different factors affect user acceptance of pooled ridesharing in the next phase.

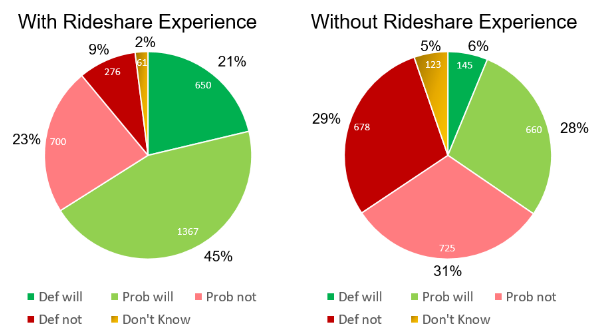

Figure II.1.10.6 Willingness of PR after meeting needs

Results of In-situ Human Factors Study Design in Pooled Rideshare

To prepare for the human factors study on in-situ pooled rideshare experiences, prior to survey data collection the team built a recording system which uses an omnidirectional camera to record in-situ video and audio scenarios inside a real vehicle. A headrest-mounted camera setup was developed to attach the omnidirectional camera in the seating area, approximating the location of an occupant's head. This can be used to record various in-situ pooled rideshare scenarios which participants will be able to experience in the future. At the same time, we have developed pooled rideshare experience rendering approaches to render the recorded experience for participants in which the recorded pooled rideshare videos are rendered via either screens or a virtual reality headset while the recorded audios are rendered through speakers or headphones. This will enable participants to experience different in-situ rideshare experiences. This design not only can be used for the in-situ human factors study, but also for the later experimental evaluations of new rideshare technologies.

In addition, we have started the design of in-situ scenarios to help improve pooled rideshare. Based on the results of the survey-based study, two of the greatest factors affecting willingness to consider pooled rideshare are safety and privacy concerns caused by the implications of COVID pandemic and interacting with unknown riders. Currently, the team is developing a model for passenger partitions, a potential solution that addresses both factors. The partition will be able to separate riders in the vehicle. The current design of the partition is a transparent pane of acrylic. We plan to additionally adhere polymer dispersed liquid crystal (PDLC) film over the acrylic panel. The PDLC film is powered electrically. When PDLC is turned off, the film will appear frosted and opaque, providing privacy between occupants. Passengers will have the option to turn on the film, which will cause the film to appear transparent. This will allow passengers to meet and converse if desired. This is one example for future in-situ scenarios to see if this addresses the safety and privacy concerns to improve user acceptance of pooled rideshare.

Results of Simulation of Pooled Rideshare in POLARIS

The team have extended the agent-based, activity-based POLARIS travel demand model to include modularity in modeling pooled rideshare vehicles and its operations in which traffic, ride hailing, and pooled users are simulated. The structure of the simulation is shown in Figure II.1.10.7. With modularity in place, the survey results and models from previous milestones can be incorporated into the simulation framework seamlessly. The implementation has also supported heuristic pooling operations (assuming all pooled trips) and combines a smooth input-to-output step so that data is crunched appropriately into metrics widely used in shared mobility research (such as average response times, person-level delays from pooling a ride, changes in total vehicle-miles traveled, average occupancy weighted by distance or trip, empty or deadheading miles, etc.). Furthermore, a prototype framework for pooled rideshare choice has been developed. This prototype currently supports querying traveler choice to pool or not to pool once the decision to use a shared vehicle is made. Zone-level metrics typically found to be predictive of pooling are made available from the start of the simulation. Further, person-level socio-demographic data is available from the synthetic population like data obtained in the U.S. Census. Pooled rideshare acceptance model that is to be developed based on human factor study results will feed directly into this prototype framework with modifications as needed to utilize latent variables obtained in the survey.

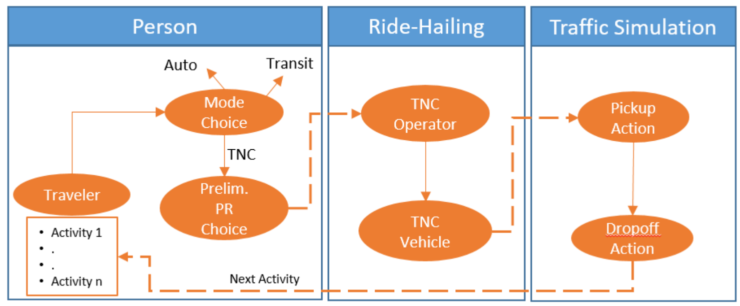

Figure II.1.10.7 Simulation of pooled rideshare in POLARIS

In addition, the team have been building the simulation of Greenville in POLARIS. Based upon the POLARIS required inputs we have collected the necessary data to begin simulating Greenville in POLARIS. These data will allow us to simulate the traffic of Greenville with high fidelity in POLARIS and observe how traffic is moving in the area and how adding a ridesharing service could affect it. We have collected the census data, public transit data, and important network files for the Greenville area. We have also ensured preliminary compatibility with POLARIS. In addition, we have increased the resolution in demographic and land use data sets, included the city points of interest (POIs), and created file download scripts for increased automation potential in current and future POLARIS data collection processes. Figure II.1.10.8 shows the Greenville region that will be simulated in POLARIS with points of interest data highlighted.

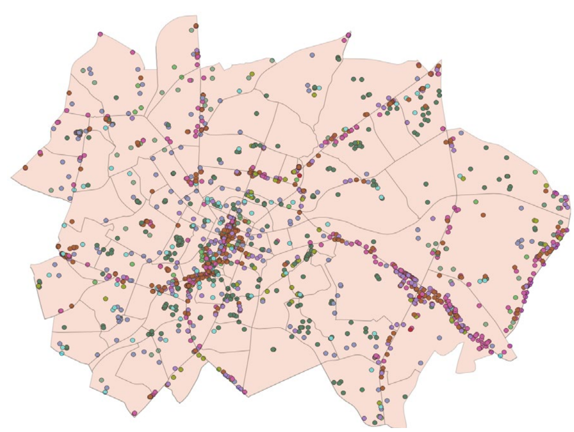

Figure II.1.10.8 Simulation of Greenville in POLARIS

Results of Autonomous Pooled Rideshare Vehicle Development

The team acquired three vehicles as the platforms for this work including an electric vehicle Nissan Leaf (sedan), a gasoline vehicle Mazda CX-7 (SUV), and a hybrid vehicle Chrysler Pacifica (minivan). These vehicles have modalities in both powertrains (i.e., electric, gasoline, hybrid) and vehicle types (e.g., sedan, SUV, minivan) to provide diverse pooled rideshare experience. The vehicles are shown in Figure II.1.10.9. Pooled rideshare technologies will be implemented on these vehicles to conduct usability studies with participants. We will especially emphasize the autonomy features on these vehicles to target future autonomous pooled rideshare service.

The hybrid Pacific has been retrofitted with a drive-by-wire system, fully equipped automated driving sensors, and some basic automated driving functions. We are also retrofitting the electric leaf and gasoline CX-7 vehicles to be autonomous driving using our self-developed automated actuation system including steering and pedal control robots to control the steering, throttle and brake pedals, a suite of autonomous driving sensors and autonomous driving algorithms for pooled rideshare vehicles.

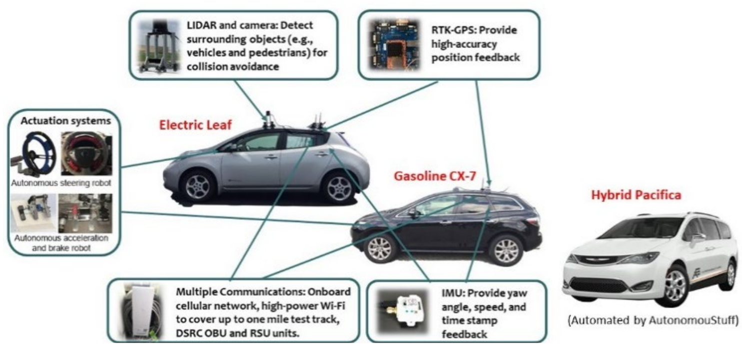

Figure II.1.10.9 Multi-mode autonomous pooled rideshare vehicles

We have integrated this GNSS into our existing low-level speed controller and tested the vehicle on an open road. The results show that the vehicle can automatically track the desired speed well and follow the desired waypoint trajectory for future rideshare routes. In addition, we have improved the longitudinal controller of the vehicle to give it a better acceleration tracking performance. On top of this, we added and tuned a closed-loop-speed-and-acceleration control mode to the lower-level controller such that it can accommodate all possible commands from POLARIS in the future. For the lower-level steering controller, we are conducting multiple road tests and improving the control algorithm to reduce oscillation and trajectory tracking error issues seen in previous tests. We have also been developing the communication interface between physical vehicles and POLARIS. The interface is responsible for establishing stable wireless communication channels for exchanging data between the POLARIS and the real vehicles including reading commands from and sending the vehicle sensory information to POLARIS in real time.

Impacts of COVID-19 and Foreign National Approvals

The delays of foreign national approvals have postponed the involvement of the PI for about half a year and the involvement of other foreign nationals including all PhD students at Clemson University for almost a year. The COVID-19 pandemic postponed the deployment of the survey until July 2021 when President Biden predicted a return to normalcy. Starting data collection prior to that date may have biased the results. Therefore, the progress of the project has been significantly affected and a no cost extension will be requested to complete the proposed work.

Conclusions

We have completed the survey-based human factors data collection. We designed the survey based upon a comprehensive review of the state-of-the-art to explore the factors which may affect user acceptance of pooled rideshare. We deployed the survey national wide and collected 5,385 responses and targeted cities/areas with an even distribution of genders and ages.

We conducted a preliminary analysis on the user acceptance of pooled rideshare and factors which may affect user acceptance of pooled rideshare. The results indicate that many users may be willing to consider pooled rideshare, but they may have concerns that need to be addressed. Therefore, we will need to further investigate how different factors affect the user acceptance of pooled rideshare through the following human factors study. Furthermore, it shows that personal safety, travel cost, convenience, reliable transportation, and travel time are the top five general factors, and these factors also vary for different groups who would like or would not like to consider pooled rideshare. A deeper analysis of the data is being conducted and the results will be used to guide the next human factors study.

We have developed pooled rideshare modules into POLARIS to simulate pooled rideshare. A prototype framework for pooled rideshare choice has also been integrated. In addition, we have built simulation of Greenville in POLARIS to not only expand the capability of POLARIS but also support future validations with people in Greenville. We will continue to incorporate the to-be-developed realistic pooled rideshare acceptance models and technologies into POLARIS to create high-fidelity simulation validations.

At last, we have acquired three vehicles to build pooled rideshare vehicles for experimental validations covering modalities in powertrains (i.e., electric, gasoline, hybrid) and vehicle types (e.g., sedan, SUV, minivan). In addition, we have focused on developing autonomy functions for building future autonomous rideshare vehicles. We will continue to improve and test the autonomy functions and develop communication interfaces between these vehicles and POLARIS.

Key Publications

1. "Human factors considerations and their impact on pooled rideshare." Technical Report, 2021.
2. "A national survey investigating human factors obstacles to pooled rideshare." In preparation.
3. There is no officially published articles yet in the first year.

Acknowledgements

The Principal Investigators would like to acknowledge the critical work of the other members in this project: Kristin Kolodge and Lisa Boor from J.D. Power, Joshua Auld and Krishna Murthy Gurumurthy from Argonne National Lab, James Fishelson from Ford, and Casey Jenkins, Noah Cooley-Cannon, Elenah Brielle Rosopa, Timothy Jenkins, Joseph Paul, Haotian Su and Rakesh Gangadharaiah from Clemson University.

II.1.11 AI-Based Mobility Monitoring System and Analytics Demonstration Pilot (UCI)

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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 cooperative driving automation (CDA) technologies has seen steady growth since the turn of the 21st century with cellular communications providing ever-increasing vehicle telematics capabilities alongside the concurrent development of direct V2I and V2V technologies (collectively known as vehicle-to-everything, V2X) focused originally on the Dedicated Short Range Communications (DSRC) standard and associated application stack and standards designated by the DOT’s Architecture Reference for Cooperative and Intelligent Transportation (ARC-IT). More recent developments have seen solutions built upon competing or compatible standards including cellular V2X and 5G cellular technologies.

It is generally recognized that the success of connectivity technology requires sufficient market penetration of CDA-enabled vehicles. Local benefits, particularly related to safety improvements, are possible with limited deployments. However, attainment of efficiency benefits in terms of reduced delays and energy use that are significant at the system level requires a market penetration rate that is orders of magnitude larger than realized today in the United States [1] where only a handful of OEMs have committed to deploying connectivity technology, and the number reducing due to regulatory uncertainty.

Figure II.1.11.1 Left: AI-based system installed on signal light post
Right: Representative AI-based system reading of an intersection

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 [2]. An emerging CDA technology, an "AI-based 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. Distinct advantages of the AI-based system include one unit per intersection and preclusion of privacy constraints. These and other benefits, summarized in Table II.1.11.1, are notable.

Table II.1.11.1 Summary of "AI-Based System" Technology Benefits

Benefit	Description
Multimodal	Detecting all road users including vehicles, pedestrians and cyclists whereas incumbent systems (like radar & inductive loop detectors) are built to see vehicles only.
Reliable	Operating in all weather and lighting conditions, whereas other multimodal systems (like camera-based solutions) are highly dependent on weather and lighting.
Real-Time	Creating a 3D map of an entire intersection without post-processing.
Automated	Fully automated.
Easy, Low-Cost Installation	One sensor per intersection that can be installed on the same pole as the traffic cabinet.
Multi-Purpose	Stakeholders can use for several purposes including traffic light control and optimization, traffic studies, and safety analysis.
Private	Eliminates privacy concerns of current camera-based systems.
Safety	Detects incidents and immediately notifies emergency departments for faster, more efficient response; can also detect spikes in or high levels of near misses.
Environmental, Social, Governance	Potential to reduce congestion by 20-30%, address 50% of traffic injuries, and reduce emissions by 5-15%.
Communication	Equipped for V2X communications with CDA-enabled vehicles and infrastructure.

The proposed project will demonstrate and evaluate an AI-based 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. It is 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 mobility energy productivity (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 Argonne National Laboratory, 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.

Impacts of the technology include improvements in energy efficiency, traffic efficiency, safety, and air quality. 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

The recipient will develop a portfolio of Controlled Traffic Events to demonstrate the capability of the proposed AI-based system and CDA-enabled vehicles. Vehicles will then be simulated performing these traffic events and the resulting energy and traffic efficiency and safety and emissions impacts will be analyzed to ensure at least a 15% improvement in energy efficiency is achievable. The recipient will analyze the potential locations for 25 AI-based systems and select locations that satisfy project needs along with those of the relevant permitting agencies. Permitting for installation of the systems at those locations will be secured, the sensors will be procured, and the three fleets (individual-use, shared-use, and Mobility as a Service) will be prepared for outfitting through procurement of the individual-use and autonomous fleets and installation and commissioning of data logging and connectivity technologies. Lastly, the XiL experiment setup will be prepared.

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 Controlled Traffic Events 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.

Figure II.1.11.2 Argonne National Laboratory Advanced Mobility Technology Laboratory (AMTL)

The recipient will perform the portfolio of Controlled Traffic Events. Data from the deployment including Free Driving and Controlled Traffic Events 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

The progress on this project had not reached the results stage at the end of FY2021.

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II.1.12 Next Generation Intelligent Traffic Signals for the Multimodal, Shared, and Automated Future

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Start Date: August 19, 2019 End Date: August 18, 2021
Project Funding: $1,000,000 DOE share: $1,000,000 Non-DOE share: $0

Project Introduction

Significant energy efficiency and greenhouse reduction gains can be achieved with better management of traffic flow, but 98% of the U.S. signalized intersections still use antiquated fixed timers to dictate their timing, resulting in static systems that fail to accommodate real-time conditions.[2] Adaptive Traffic Control Systems (ATCS), which adapt signal timing based on real traffic conditions, have only been adopted in ~2% of U.S. intersections over the last 30 years. The primary reasons are high cost due to expensive sensor infrastructure (average $65,000 per intersection) and limited effectiveness due to simplistic and antiquated algorithms. Incumbent ATCS technology providers consume poor quality data from local sensors like induction loops or video cameras, rely almost exclusively on centrally controlled mechanisms that stifle scalability, are significant security liabilities (single point of failure), and focus on optimizing offsets on a narrow set of road arteries, rather than the full transportation network.

This project engages in live-intersection research and validation of a novel ATCS algorithm to optimize traffic signal performance. The research falls under the market term "Cooperative Intelligent Transport Systems" (C-ITS) and represents a unique approach that can significantly reduce transportation network energy consumption by widely deploying the latest control algorithms in conjunction with emerging technologies to address key hurdles preventing wide-spread adoption of adaptive ITS technology: efficacy and cost.

The core algorithms are inspired by information technology network throughput maximization techniques; They are inspired by the routing and scheduling methods which dictate how packets of information flow efficiently over telecommunication information networks. Based on PTV VISSIM simulations, the proposed proportionally fair classes of optimization algorithms, combined with additional real-time data (connected vehicle, telecommunications carriers, mobile applications, etc.), have the potential to increase vehicle throughput through transportation networks by up to 50% over the best incumbent technologies, while substantially reducing the capital investment cost by up to 90%.

However, current benefits estimated through detailed modeling and simulation must be validated through actual real-world experiments. Xtelligent has installed the system in live city intersections in Colorado and California and has been testing aggressively. Successful validation of this research will confirm the positive effects of the proposed high efficacy /low-cost C-ITS concept. Mass adoption of such a system across U.S. intersections could result in 373 million gallons of fuel saved, 3.7 megatons of CO_2 equivalent greenhouse gases, and 2.5 billion hours of time saved each year alone.

Objectives

The core goal has remained the same: to research, develop, and evaluate the proportionally fair traffic signal control algorithm in a real-world setting. With Phase II SBIR funding, we set out to finalize system design for coordinated ATCS control, deploy across a wider city network of 100 contiguous intersections, and test the inclusion of real-time streaming vehicle location data from internet-based sources (rather than physical sensors).

We had previously demonstrated a 50% throughput improvement in PTV VISSIM microsimulation modeling environment which is expected to yield 15% improvement in energy efficiency, but the simulated environment does not provide for all the unforeseen variables that only the real-world setting can provide. Real-world validation is also necessary before additional financial and human resources can be committed for the commercialization of the researched algorithm. The SBIR scope of work will also help quantify the energy impact of the technology for different market penetration.

- Objective 1: Coordinated ATCS Control for Throughput Maximization:
  - Xtelligent's novel traffic signal control algorithm will be fully tested across a complex grid of coordinated intersections while relying on in-road physical sensors. The goal is to activate up to 100 intersections simultaneously for a broad system test.
- Objective 2: Evaluate novel vehicle location data sources in combination with traditional physical sensor data as inputs to Xtelligent's ATCS.
  - Potential data sources under evaluation include connected vehicle automotive manufacturers, telecommunications service providers, smartphone application companies, smart phone manufacturers, 3rd party traffic data aggregators, and other data sources. Each is expected to have different characteristics, including varying precision, latency, penetration, and transmission frequency. Duplicated data will need to be removed, temporal differences aligned, varying levels of accuracy/precision accounted for, and the behavior of unconnected/ "unseen" vehicles inferred from the smaller population of "seen" vehicles. Based on Xtelligent's discussions with industry partners, we anticipate 20-40% penetration of location-aware vehicles across the full population of vehicles.
- Objective 3: Performance Improvement by Supplementing Existing Physical Sensor Data with Connected Vehicle Location Data (V2I using 4g/LTE)
  - Existing Xtelligent pilot sites include some physical sensors already present in the roadway. These sensors suffer from two major categories of limitations: technical and commercial. From a technical standpoint, the induction loops and video systems provide limited data: binary vehicle presence information at small zones (6 ft) at the stop bar or slightly upstream and are unaware of estimated times of arrival or volumes of approaching vehicles. Critical measurements like queue length must be inferred and are not measurable by today's sensor systems. They are primarily designed to supply data to actuated intersections and are not well-suited to high performing adaptive control. Rigorously test before/after system performance to determine energy efficiency benefit to transportation network of including this additional data.
- Objective 4: Attempt to maintain or improve system performance using only novel location data streams.
  - This objective involves Xtelligent's unique, proportionally fair ATCS control with full reliance on streaming location data without any use of in-road, physical sensors.
- Objective 5: Evaluation of Beta/Pilot

- Includes detailed data analysis and reporting of the live deployment data. This data will also be supplied to Argonne National Laboratory, which will then execute its subaward work to quantify the energy reduction effects of the traffic management system.

Approach

To achieve the research objectives listed above, Xtelligent first identified a set of potential pilot 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 20 contiguous intersections, and 4) an enthusiastic and innovation-minded set of public works/transportation staff willing to partner with this effort. The Colorado Department of Transportation, City of Greenwood Village, CO, and Fremont, CA were selected as sites.

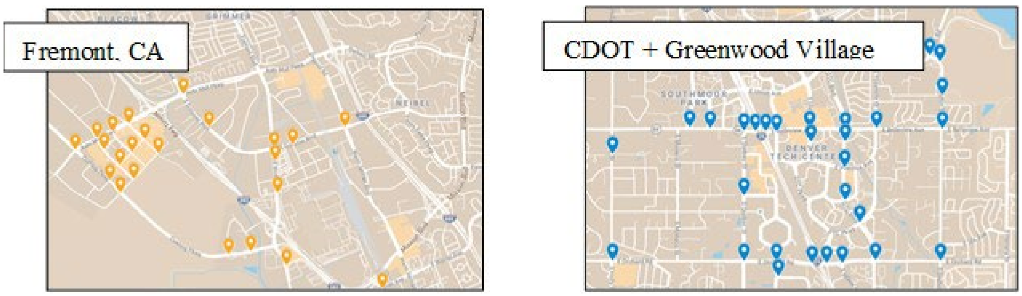

Figure II.1.12.1 Transportation Agency Pilot Sites

The next effort involved integration with the Siemens, Intelight, and Econolite controllers across these three agencies. This integration required a significant amount of software development effort to understand the nuanced implementation of NTCIP across several controller manufacturer types, but this effort has resulted in a smoothly interoperable system that represents the first interoperable system of its kind globally. This is especially important given the U.S. government's push for standardization to protect public transportation authorities from vendor capture and making it possible for innovative researchers and companies to more easily deploy and test innovative control algorithms across multi-jurisdictional regions. Xtelligent also constructed an off-line signal laboratory to iterate integration development more quickly. The lab includes McCain, Intelight, Econolite, and Siemen's controllers, and is accessible remotely by secure VPN. This setup has also proved helpful keeping the research team productive during the ongoing COVID-19 pandemic.

Upon system installation, we also needed to validate the limited physical sensor data available to us. While the original PTV VISSIM simulations undertaken had the benefit of perfect simulation data, traditional traffic signal systems rely on induction loop and/or video camera data, which only gives occupancy and volume information based on vehicle presence in a single sensor location—typically at the stop bar of an approach, and sometimes in an "advanced" configuration a few hundred feet from the stop bar. Extensive mathematical correlations needed to be completed comparing recorded CCTV video data with sensor data logged from the controllers. Xtelligent was able to validate these algorithms to create suitable inputs for the Proportionally Fair ATCS algorithm used in this research.

Next, to complete Objective 1 Xtelligent began activating its novel traffic signal control algorithm across single intersections and corridors to validate performance. The specific approach required at least 5 days of baseline data, which was compared with 5 days of adaptive testing data. This allowed for a close baseline with enough cycles to generate statistically significant results.

In parallel with controller integration software development, Xtelligent's leadership team extensively researched appropriate internet-based location data streams to include as inputs per Objectives 2 through 4. The streaming data evaluation results are tabulated in "Results" below. The Covid-19 pandemic heavily affected the availability of these data streams, as automotive OEMs and other partners temporarily reprioritized their corporate focus to address supply chain shortages. Xtelligent is working towards data partnerships with five automotive connected vehicle manufacturers, two telecommunications service providers, two traffic data aggregators, and two smart phone application companies. Xtelligent has also just opened a 3rd pilot site in Long Beach, CA, in partnership with a co-located automotive OEM test fleet for the use of streaming location data in our adaptive traffic signal control algorithms.

Finally, the comprehensive set of baseline and test research data will be analyzed in detail by Argonne National Laboratory's transportation simulation group. We will collectively be determining the results of our tests and simulating the extrapolation of these results across a major metropolis. This final effort is still being completed by the national laboratory. The increase in transportation network energy productivity, greenhouse gas emissions reductions, travel time savings, throughput increases, and any other available metric will be studied and submitted in the final SBIR project report.

Results

This annual progress report represents the conclusion of the second 12 months out of a 24-month period of performance under this grant. A significant amount of foundational work has been completed to implement a real-world, in-street ATCS system to research and develop Xtelligent PF ATCS. COVID19 impacts to vehicular congestion levels and partner transportation agency priorities caused a material impact on project timeline.

Technical results to date include over 100 in-street tests as the system design is iterated, an evaluation of real-time streaming data source quality, and the design of a user interface to help transportation engineers understand the performance of their transportation networks.

A) Single intersections activations in 2019: At the end of Phase I, Xtelligent was able to demonstrate successful implementation of its PF ATCS solution in single, non-coordinated environments. Because single-intersections effectively represent a network of one node, we use green-time utilization (or the inverse, "slack ratio") as the representative metric. Green-time utilization is the percent (%) of green-time utilized, and is correlated to throughput and traditional transportation metrics like travel time, delays, arrivals on red, level of service, etc. Key focus was ratio of green-time utilization between major through-phases (2 and 6) and side phases (4 and 8). Perfect balance would be indicated by a Slack ratio of 1.00

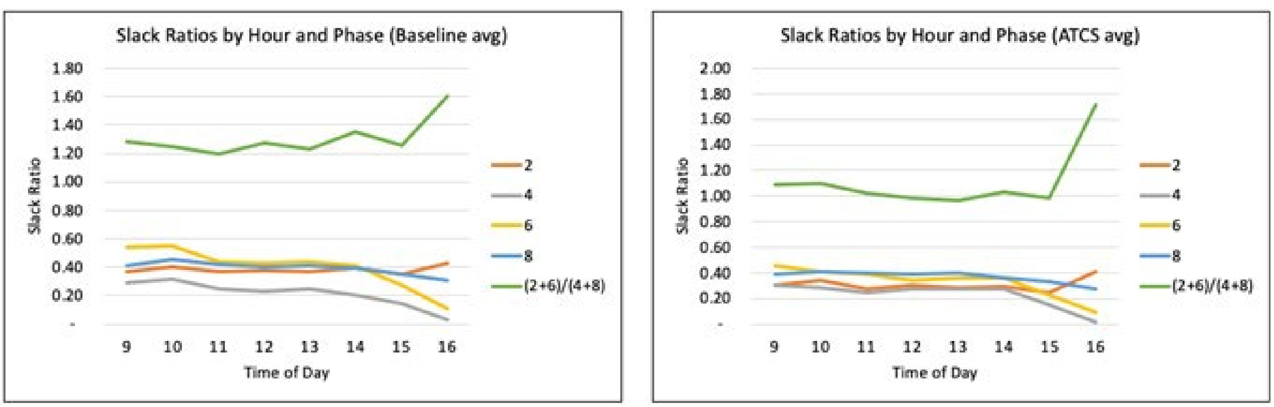

Figure II.1.12.2 Performance improvement in single (non-coordinated intersections) *

In the charts above "Slack ratio" represents proportion of green time not utilized. Most phases exhibited 0.40 unused green time. Baseline ratio of main phases to side phases (2+6)/(4+8) = 1.30. When activating Xtelligent's PF ATCS, the ratio of main phases to side phases (2+6)/(4+8) = 1.09, a 21% improvement.

*Tests deactivated daily at 1600. Spike at 1600 due to restoration of city control

B) Coordinated intersection activation testing began in summer 2020 continuing through the grant end date in August 2021 and beyond. COVID-19 greatly impacted traffic volumes, affecting relevant real-world baselines for research validation. The deepest reduction in traffic volumes approached 80% in April 2020 and remains down approximately 20% in November 2021. In addition, several agencies temporarily converted their usual Time of Day (TOD) coordination plans along corridors to a free-mode policy to accommodate the unusual, eclectic traffic volumes. Xtelligent successfully tested its system against this scenario, showing a 26% improvement in system performance. Our next efforts are focused on validating the system against a more robust, TOD baseline.

The below table includes Xtelligent's PF ATCS performance data from 8/10/20 – 8/14/20 as compared to a baseline data set on the same corridor from 8/3/20 – 8/7/20, using a variant of the sum of induction loop occupancy times per phase per hour for each type of system. A reduction in hourly sum of this demand on each phase denotes a reduction in congestion and a more optimal traffic signal timing scheme. Changes in aggregate traffic volumes were also compared between baseline and ATCS weeks to account for any changes resulting from this alone.

8/3 - 8/7 Baseline (Free mode)

	Phase						
Hour	3-Aug	4-Aug	5-Aug	6-Aug	7-Aug	Stdev %	Avg
9	6,369	5,886	6,281	6,093	6,343	3%	6,194
10	5,951	6,373	6,633	6,554	6,619	4%	6,426
11	6,934	6,857	6,906	6,801	6,674	2%	6,834
12	6,581	6,528	6,739	6,813	6,960	3%	6,724
13	6,300	6,210	6,447	6,531	6,810	4%	6,460
14	7,088	7,590	6,929	7,089	7,446	4%	7,228
15	8,654	8,007	7,972	8,256	8,251	3%	8,228

8/10 - 8/14 PF ATCS

	Phase							
Hour	10-Aug	11-Aug	12-Aug	13-Aug	14-Aug	Stdev %	Avg	Δ
9	4,370	4,251	4,148	4,452	4,492	3%	4,343	30%
10	5,135	5,408	4,808	5,522	5,105	5%	5,196	19%
11	4,775	4,915	4,930	6,011	5,082	10%	5,143	25%
12	4,343	4,892	4,952	5,353	4,834	7%	4,875	28%
13	4,604	4,759	4,885	4,693	4,933	3%	4,775	26%
14	4,948	5,493	5,691	5,172	5,517	6%	5,364	26%
15	5,972	6,412	5,835	6,578	5,635	7%	6,086	26%

Figure II.1.12.3 Performance improvement from free mode corridor baseline (2020)

As Covid-affected traffic volumes partly restored and our agencies restored their standard, coordinated TOD plans, Xtelligent was able to devote 2021 to extensive, iterative testing. We have generally followed a one week on/one week off testing pattern, using the "off" week to analyze the previous weeks' data and adjust our algorithm assumptions to improve performance. Performance improvement results against a TOD baseline have achieved a maximum, statistically significant 17% improvement in late May 2021 using the same analysis techniques detailed above. Several weeklong tests also yielded flat improvement, suggesting a focus on improving consistency of results was a prudent requirement. Since then, Xtelligent has devoted its research to adjusting various input parameters to improve consistency of the positive results.

5/17 - 5/21 Baseline (coordinated mode)

	M	T	W	R	F	Stdev %	Avg
Hour	17-May	18-May	19-May	20-May	21-May		
9	14,795	14,832	15,881			4%	15,169
10	14,072	14,964	16,543			8%	15,193
11	15,581	20,409	17,029			14%	17,673
12	16,322	19,663	18,335			9%	18,107
13	15,902	19,084	18,604			10%	17,864
14	17,637	19,461	19,671			6%	18,923
15	20,190	21,232	21,876			4%	21,099
16	20,135	22,806	23,886			9%	22,276
17	21,996	23,197	23,107			3%	22,767
						7%	18,786

5/24-5/28 ATCS

	M	T	W	R	F			
Hour	24-May	25-May	26-May	27-May	28-May	Stdev %	Avg	Δ
9	12,741	13,842	13,181			4%	13,254	13%
10	13,922	13,411	12,674			5%	13,336	12%
11	16,390	13,581	14,473			10%	14,815	16%
12	16,295	15,231	14,109			7%	15,212	16%
13	13,832	13,982	14,997			4%	14,270	20%
14	15,932	16,154	14,633			5%	15,573	18%
15	15,733	16,268	17,263			5%	16,421	22%
16	17,710	18,305	18,722			3%	18,246	18%
17	17,449	17,704	18,560			3%	17,904	21%
						5%	15,448	17%

Figure II.1.12.4 Max performance improvement from TOD corridor baseline (2021)

C) Over the course of the grant period of performance, Xtelligent aggressively pursued location data partnerships to achieve objectives 3 and 4: integration of these data streams into the PF ATCS test bed. However, the Covid-19 pandemic significantly affected the attention and priorities of location data partners, in particular automotive OEMs with connected vehicles, who needed to significantly curtail and restructure their R&D efforts/teams due to the pandemic. As a result, Xtelligent was unable to integrate streaming location data into its testing platform by the end of the grant period of performance, but it remains a focused priority of the company. Despite this, we were able to develop strong relationships and evaluate the state and quality of the various potential data streams for future inclusion. Key variables for each data stream are % penetration, % accuracy, data latency, and ease of partnership. Due to non-disclosure agreements, all names must remain obscured. Preferred data streams appear to be 1-4, 5, and 10. The table below in Figure II.1.12.5 reflects the latest status of data partner evaluation.

	Data partner	% Penetration (of vehicles)	Accuracy	Latency	Partnership potential	**Status**
1	Connected Vehicles: OEM 1	<1%	2m	30 sec	Medium	COVID reprioritizations delayed past grant timeline
2	OEM 2	<1%			Medium	COVID reprioritizations delayed past grant timeline
3	OEM 3	0-5%[1]			High	App requirement is not realistic for commercial use
4	OEM 4	~4%			High	Low penetration and high cost: not a viable source for now
5	Telecom 1	30%	100m	>1 min[2]	High	Committed partner, but no site overlap
6	Data Aggregator 1	10%	~50m	1-15 min[3]	Medium	High latency and "smoothed" data is not high potential
7	Data Aggregator 2				Medium	High latency and "smoothed" data is not high potential
8	Data Aggregator 3				Medium	High latency and "smoothed" data is not high potential
9	Xtelligent's App	0%	2m	1s	High	App requirement is not realistic for commercial use
10	Map Provider	>20%	2m	TBD	Medium	Large organization; timeline to focus on this effort is long

Figure II.1.12.5 Data Partner Evaluation Result

The likely first site for testing of the combined data pipelines listed above is Long Beach, CA. City Council approved the pilot project on September 15, 2020, and after lengthy administrative negotiations the project has finally kicked off in November 2021.

Conclusions

In conclusion, Xtelligent has used the second half of its SBIR Phase II period of performance effectively to continue developing real-world pilot sites where it is regularly testing its PF ATCS novel algorithm, showed strong maximum results against a TOD baseline, and has evaluated streaming location data potential for future inclusion as optimization algorithm inputs. The impact of COVID-19 on our data partners as well as the ability to test and iterate on real-world traffic conditions introduced significant delays, but the team was able to largely overcome these and is poised to continue progressing towards algorithm development, innovative data stream integration, and validation milestones.

Acknowledgements

Acknowledging Michael Lim, who has been instrumental in developing and managing our city/agency partnerships. These real-world pilot sites are instrumental to Xtelligent's DOE funded research, and his support has been invaluable.

II.1.13 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: December 31, 2023
Project Funding: $2,306,858 DOE share: $1,750,155 Non-DOE share: $556,703

Project Introduction

Transportation accounts for 28% of the total energy use in the U.S. It is responsible for immense environmental impact, including urban air pollution and greenhouse gas emissions, and may pose a severe threat to energy security. Switching from personal vehicles to public transit systems can significantly reduce energy use and environmental impact. However, even public transit systems require substantial amounts of energy; for example, public bus transit services in the U.S. are responsible for at least 19.7 million metric tons of CO_2 emission annually. Electric vehicles (EVs) can have a much lower environmental impact than comparable internal combustion engine vehicles (ICEVs), especially in urban areas. Unfortunately, EVs are also much more expensive than ICEVs (typically, diesel transit buses cost less than $500K, while electric ones cost more than $700K, or close to around $1M with charging infrastructure). As a result, many public transit agencies can afford only mixed fleets of transit vehicles, consisting of EVs, hybrids (HEVs), and ICEVs. To compound the problems, the transit agencies must balance the tradeoff between concentrating service into high-utilization routes that serve large numbers of people and spreading out service to ensure that people everywhere have access to at least some service. These challenges are exacerbated by the requirement to provide complementary paratransit services, which are typically characterized by very low efficiency and attendant high cost of operation.

As agencies scale their systems and increase the ratio of EVs in their fleets, another concern arises that they must address—considering the impact of charging their EVs on the power grid in their service area. Answering this question is critical as the locations of charging stations needs to be strategically chosen to reduce nodal losses. Further, electric utility operators must balance the distribution network and estimate daily needs considering variations in demand. This leads to long-term and short-term decision problems that must be addressed. The long-term problem is to choose the locations of charging stations, while the short-term online problem is the strategic, collaborative optimization between transit agencies (and potentially other operators of EV fleets) and the utility operator. The utility operator can change the pricing at each location, while fleet operators can change their charging schedules. Solving these problems requires real-time information from sensors and dynamic, online decision solutions.

Our hypothesis is that there is a significant opportunity for lowering the overall energy cost if we focus on systemwide integration, which co-designs the schedules and services of fixed-route transit, microtransit, and paratransit. In particular, we observe that transit agencies can solve the problems at four levels: (a) deciding the area and frequency of fixed-route trips, (b) deciding the areas and types of trip requests that can be served through integrated paratransit and microtransit operations, (c) optimizing the vehicles that are used for each trip, considering that the advantage of EVs over ICEVs varies depending on the route and time of day (e.g., the benefit of EVs is higher in slower traffic with frequent stops and lower on highways) and that the assignment can have a significant effect on energy use and, hence, environmental impact, and (d) finally working with the local electric utility companies to optimize the charging schedules and charger placements.

Optimizing these challenges is difficult due to the 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 (e.g., harmonizing flexible courtesy stops with on-demand transit for easy transfer). 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, etc., and many of these decisions must be made in real-time.

Objectives

In this project, we develop decision-theoretic approaches that solve the challenges. Combined with state-of-the-art sensing, big-data collection, and processing methods, our approach relies on deep reinforcement learning (DRL) 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 solutions that are more efficient 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. The micro prediction model provides estimates of instantaneous energy prediction for all types of buses (diesel, hybrid, and electric). Such a model is important in evaluating the energy impacts of real-time bus operation strategies, but it is challenging due to diversified driving cycles of transit buses. The model can help the drivers understand the impact of their driving behaviors and short-term congestions. The macro prediction models estimate average energy consumption across the whole trip considering the features: distance traveled, various road-type features, elevation change, day of the week, time of day, various weather features (temperature, humidity, etc.), and traffic features (speed ratio and jam factor).

Approach

The Vehicle Routing Problem

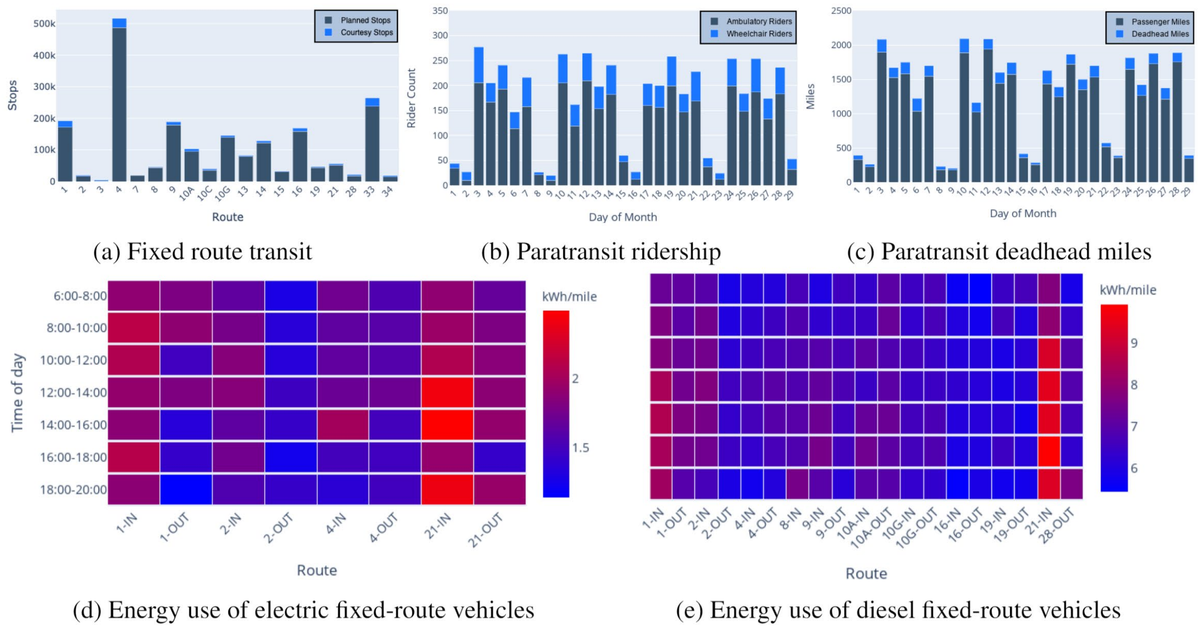
CARTA is an exemplar of the efficiency challenges that transit agencies face throughout the U.S., especially in mid-sized southern cities, where agencies must balance the tension between improving service coverage and improving ridership. CARTA spends more than $1.1 million annually on fuel while supporting several different transportation modalities, including a fixed-route service, demand-response service (using neighborhood shuttles), and paratransit service. Through these three services, CARTA provides over 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 systemwide utilization, transit accessibility, and energy efficiency.

Optimization Space

Courtesy stops allow fixed-line vehicles to stop outside of designated stops to provide flexibility and convenience to riders. While courtesy stops (Figure II.1.13.1a) are convenient, they also cause cascaded delays in service, which affect downstream trips for the riders. Maintaining a high degree of schedule reliability for each route segment is critical for the operational efficiency of the entire system. Overall, courtesy stops constitute approximately 7% of all stops, which can lead to significant uncertainty in the system. Additionally, CARTA and similar agencies operate fixed-transit fleets that mix electric, diesel, hybrid, etc. vehicles. At CARTA, the median energy consumed per mile is approximately 1.7 kWh for electric vehicles and 7.5 kWh for diesel vehicles. As shown in Figure II.1.13.1d and Figure II.1.13.1e, energy consumed per mile varies between routes and time of day.

Paratransit services are provided by transit agencies as a supplement to fixed-route services to ensure equity for disabled people, who cannot use fixed-route transportation. However, the demand varies significantly over the course of a week (Figure II.1.13.1b). One of the challenges in handling paratransit operations is the Federal Transit Administration guideline that limits the maximum wait times for passengers. Without adequate optimization procedures, most agencies add substantial slack to their schedules and limit trips to only a few passengers each, which leads to low energy efficiency. We can quantify this loss using deadhead miles, which are miles driven by paratransit vehicles without any passengers (Figure II.1.13.1c). In February 2020, CARTA paratransit vehicles were unoccupied for 10% of all miles traveled, resulting in significant energy waste. Even when occupied, average ridership was limited.

Developing scalable algorithms for real-time fleet management and operational optimization is a hard problem. Specifically, it requires solving scheduling problems that are variants of the classical Vehicle Routing Problem (VRP) and the related Dial-a-Ride Problem, which are NP-hard and typically solved using heuristic methods. While there is a long and rich literature of heuristic techniques for solving VRP problems, scalability has been an issue even for heuristic methods. Typically, scalability is handled by decomposing the VRP problem into a trip generation phase, which creates candidate trips, and an assignment phase, which assigns the fleet to a subset of the candidate trips. While this decomposition leads to increased scalability, these two sub-problems are still both NP-hard and require algorithmic sophistication.



(a) Fixed route transit (b) Paratransit ridership (c) Paratransit deadhead miles

(d) Energy use of electric fixed-route vehicles (e) Energy use of diesel fixed-route vehicles

Figure II.1.13.1 (a) Courtesy and planned stops for fixed-route transit per route from Jan. 2020 to Apr. 2020. (b) Paratransit wheelchair and ambulatory riders per day in Feb. 2020. (c) Deadhead and passenger miles per day in Feb. 2020 for paratransit vehicles. Deadhead miles defined as miles driven without passengers. (d) and (e) Average energy used in kWh/mile by trip and by the time of day for electric and diesel fixed-route transit vehicles. Scale for diesels is between 5-10 KWh/mile, scale for electric is between 0.7-3 KWh/mile. Variance shows that there are certain trips that are more energy efficient with electric vehicles than others. Also, there are certain routes like 21-inbound where using an EV will have higher impact compared to other routes. All these decisions factor into the optimization problem.

Our approach to these problems is to consider integrated on-demand scheduling and optimization within a hybrid AI-based optimization framework (see Figure II.1.13.2), which optimizes transit operations in two steps.

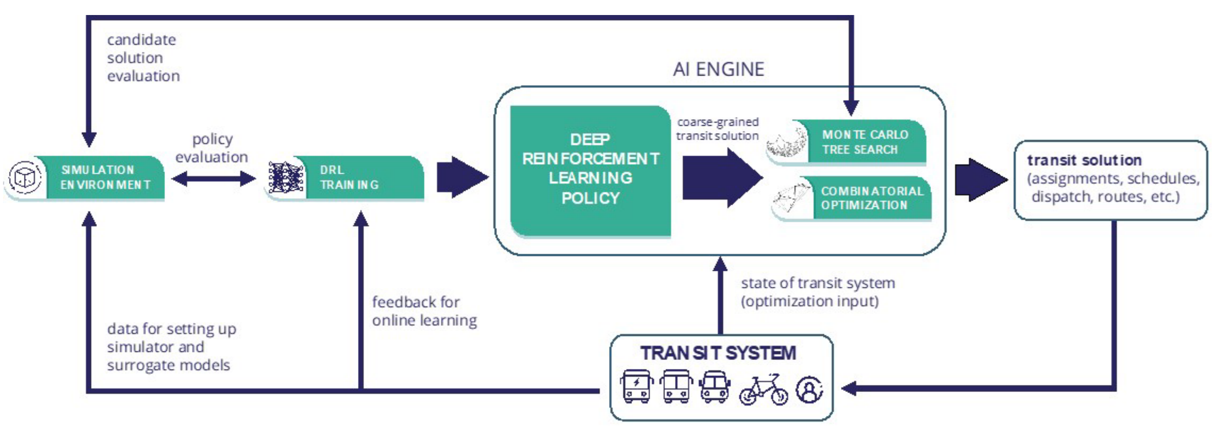


Figure II.1.13.2 Overview of AI Engine for optimization of integrated transit services

First, it uses deep reinforcement learning (DRL) to perform high-performance but coarse-grained optimization, which works on a high-level abstraction of the transit system. Second, it uses a combination of Monte Carlo tree search (MCTS) and combinatorial optimization techniques to perform fine-grained optimization, which works on a restricted solution space that is derived from the high-level solution of the first step. This framework combines the advantages of a diverse set of optimization techniques. While training a DRL policy is computationally expensive, the trained policy can be evaluated relatively easily—especially when working with a high-level abstraction—which means that the framework will be able to provide a coarse-grained solution quickly even for large transit systems. Then, MCTS and combinatorial optimization can find fine-grained, high-quality solutions on a relatively small search space.

Results

Our current progress to date includes three parts of the online integrated optimizer that arranges the paratransit dispatch trip roster. The reinforcement learning-inspired technique provides the ability to create coarse solutions as each request from a client arrives on phone (at least a night before). The technique uses a simulated-annealing method as the any-time algorithm to reduce the size and complexity of the action space. Eventually the solutions are refined using a day ahead scheduling algorithm that builds upon prior work by CO-PI Samaranayake from Cornell University [1]. The key insight is that we can use an online solver in the offline mode and avoid the complexity of computing the solution for the whole day in one shot and considering smaller time windows in a rolling horizon fashion. Finally, the real-time requests on the day of the travel are addressed using the Monte Carlo Tree search approach. Our initial results are promising and show that the heuristics can handle large vehicle capacities and provide results within a few seconds. The advantage of online scheduling is the ability to handle uncertainties and complex constraints. We are currently working on integrating the system with the fixed line schedule constraints to address the integration problem. Note that in prior work [2], the team has already developed algorithms for optimally (minimizing total energy impact) assigning vehicles of different types to fixed-route trips given predicted traffic and weather conditions and considering road elevation changes.

Simulators

Figure II.1.13.3 describes the overall concept of the integrated simulation testbed that we are building. The simulator can help evaluate the impact of different transit trips and subsequent vehicle choices and charging schedules. A key component of this concept is the transit-gym which is described next. The power grid simulator is still in the works.

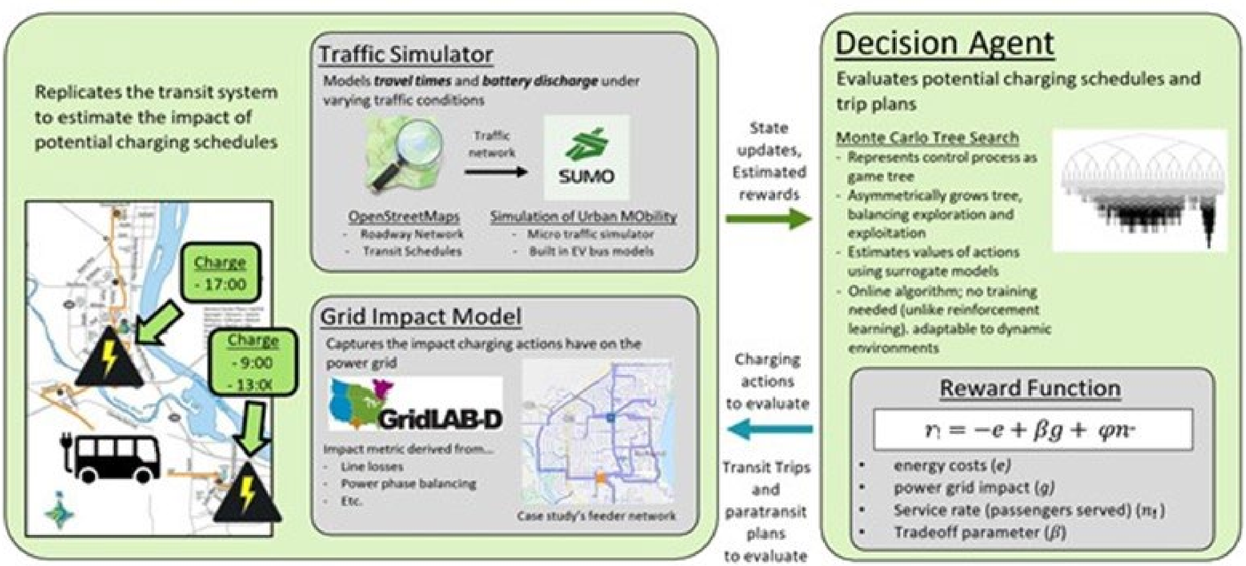


Figure II.1.13.3 Simulator Concept

Transit-Gym

TRANSIT-GYM [3] is a SUMO based general-purpose transit simulator carefully calibrated for the city of Chattanooga. This has been achieved by careful calibration of the underlying model. Note that for the simulator to remain viable, it is crucial to keep the physical transit network of the city and the simulated transit network in sync. The geometric design of roads evolves over time as new roads and additional lanes are built on existing transportation infrastructure. This adds a layer of complexity to developing precise simulation environments. It is common for developers and researchers to procure transportation data and network files from existing platforms, such as OpenStreetMap (OSM) [4]. The data available on these platforms is traditionally crowdsourced, and in many cases, it is not up to date with the actual transportation infrastructure. Therefore, we have developed and integrated specialized procedures to perform a stochastic check against the designed network and real traffic data collected from the city and then fixing any discrepancies in the network. This process ensures that that road geometries and map files are continuously updated, providing an accurate environment for testing and validation.

Figure II.1.13.4 presents the framework of TRANSIT-GYM. SUMO [5] is used to conduct microscopic traffic simulation, wherein vehicles, public transport and persons are modeled explicitly. A scenario description language that comes with the simulator provides the ability to customize the transit simulation configurations. The simulation gym is equipped with microscopic energy prediction models developed by the team [6], [7], [8] previously. They are used to estimate the energy consumption for each vehicle trip as simulated through the SUMO network.

Overall, the simulation engine can provide road-based traffic measurement output, including the macroscopic values such as the mean speed, the mean density, the mean occupancy of road edge during specified time interval. For each bus stop, we output the simulated schedule: time of arrival and departure, stopping place and number of persons that boarded and got off from the bus. The passenger itineraries are configurable and are simulated based on input demand models provided by the local transportation planning office. For each transit vehicles, we also provide current speed and acceleration. Finally, we also provide the estimated energy consumption, calculated after the simulation through the energy estimation models.

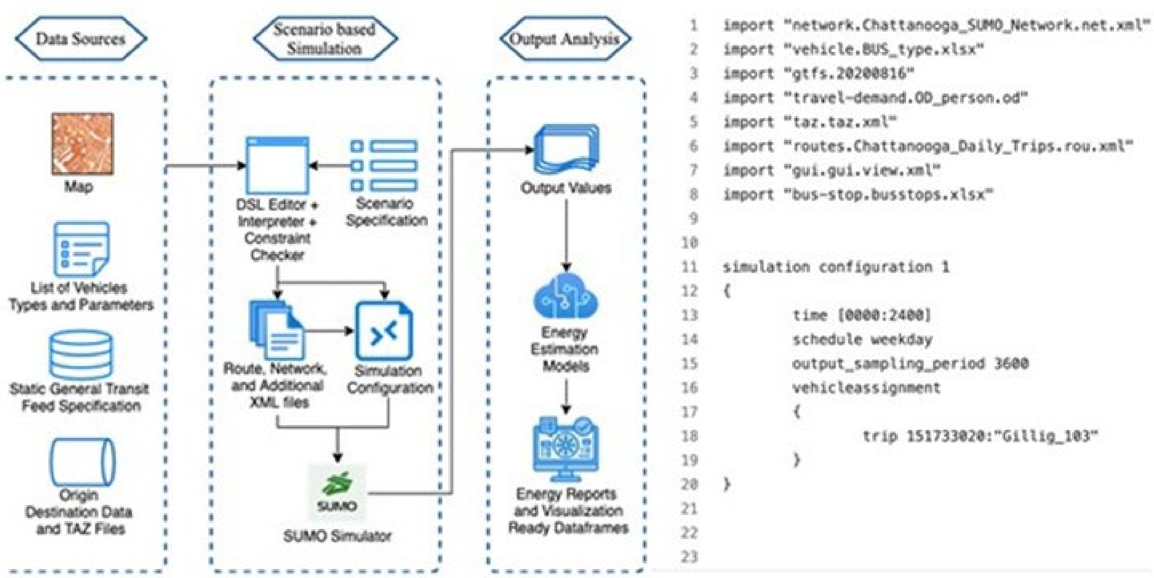


Figure II.1.13.4 Framework of Simulation Platform

Examples of the output analysis visualizations are as follows. Figure II.1.13.5 shows the passenger occupancy of each bus along its stops by trips for a whole day. Figure II.1.13.6a shows the maximum passenger occupancy of each bus along the bus stops by routes. The bar within each box represents the median of the maximum passenger occupancy of different buses on each route and the two sides of box correspond to 1st and 3rd quartile of the data for each route.

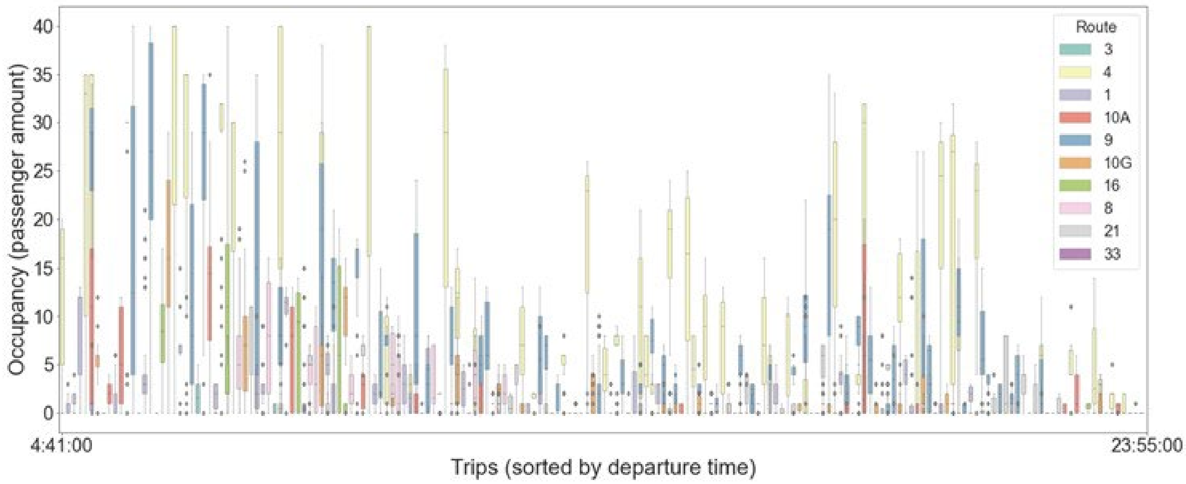
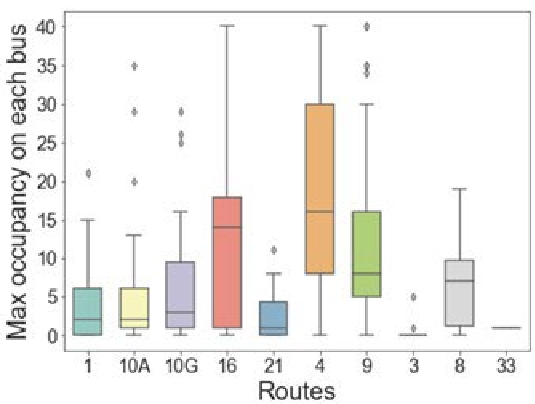
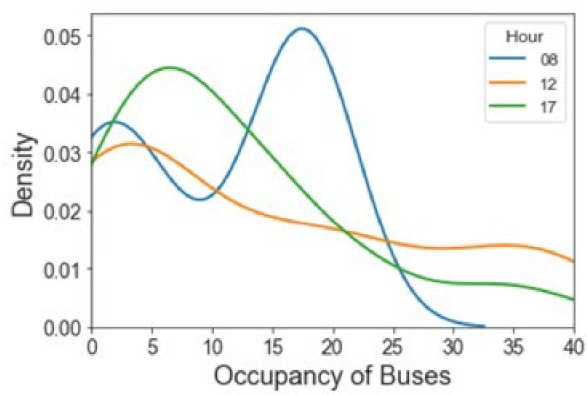


Figure II.1.13.5 Passenger occupancy of each bus along the bus stops by trips across 24 hours

To investigate the occupancy status during different time in a day, the distributions of bus occupancy between three specific hours (08, 12, and 17, according to morning, midday, and afternoon) on route 4 are shown in Figure II.1.13.6b.



(a)



(b)

Figure II.1.13.6 (a) Maximum passenger occupancy of each bus along the bus stops by routes across 24 hours. (b) Distributions of bus occupancy between specific hours on route 4

Figure II.1.13.7a shows the estimated consumption rates for buses on different routes. Figure II.1.13.7b presents the comparison of energy consumption rate of buses among different trip assignment scenarios. It shows that using all electric vehicle is the best strategy in terms of energy consumption. However, that leaves the problem of optimizing the charging schedules, which is part of the ongoing research.

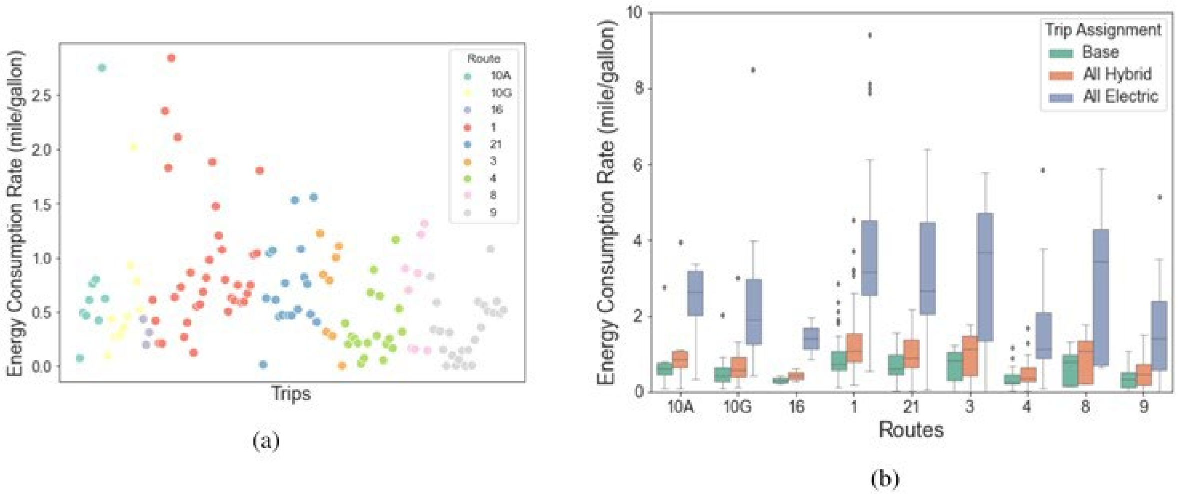


Figure II.1.13.7 (a) Energy consumption rate for buses in half a day (b) Energy consumption rate (miles per gallon) for buses in different trip assignment scenarios. Electric vehicles go longer per equivalent gallon of diesel fuel.

Datasets

Systemwide integration of scheduling and operation of fixed-route transit, microtransit and paratransit requires working with large-scale, multivariate, spatiotemporal data from a variety of heterogeneous sources. This includes streaming sensor data from buses and paratransit vans, the underlying infrastructure and road network, real-time and historical traffic, and weather to name a few. In this context, AI-driven applications and simulations require this data to be presented in a format that can be ingested by the application. Additionally, operations teams require dashboards and operational applications that synthesize and present the data in human-readable ways. Working with this data presents unique challenges of data management, processing, and presentation.

A summary of the data sources that are collected is shown in Table II.1.13.1. These data sources incorporate the available data from the fixed-line bus fleets, paratransit and microtransit vehicles, scheduling and external data sources including weather, traffic, and road network information. There are numerous challenges in storing and processing data for AI-driven urban mobility systems. First, these sources present data in domain-specific formats and at irregular intervals that can vary by provider and source, making it challenging to join data streams to be used by downstream AI models. Second, the spatiotemporal nature of these data sources presents challenges in efficient storage, synthesis, and data retrieval. A third challenge is efficiently presenting the data to AI re-searchers and transit experts for data exploration.

Table II.1.13.1 Data Sources

Data	Source	Frequency	Scope	Features	Schema/Format
Diesel vehicles	ViriCiti and Clever Devices	1 Hz	50 vehicles	GPS, fuel-level, fuel rate, odometer, trip ID, driver ID	Viriciti SDK and Clever API
Electric vehicles	ViriCiti and Clever Devices	1 Hz	3 vehicles	GPS, charging status, battery current, voltage, state of charge, odometer	Viriciti SDK and Clever API
Hybrid vehicles	Viriciti and Clever Devices	1 Hz	7 vehicles	GPS, fuel-level, fuel rate, odometer, trip ID, driver ID	Viriciti SDK and Clever API
Paratransit and neighborhood vans	Viriciti and Clever Devices	1 Hz	9 vehicles	GPS, fuel-level, fuel rate, odometer, trip ID, driver ID	Viriciti SDK and Clever API
Traffic	HERE and INRIX	1 Hz	Chattanooga and Nashville region	TMC ID, free-flow speed, current speed, jam factor, confidence	Traffic Message Channel (TMC)
Road network	OpenStreetMap	Static	Chattanooga and Nashville region	Road network map, network graph	OpenStreetMap (OSM)
Weather	DarkSky	0.1 Hz	Chattanooga and Nashville region	Temperature, wind speed, precipitation, humidity, visibility	Darksky API
Elevation	Tennessee GIC	Static	Chattanooga region	Location, elevation	GIS - Digital Elevation Models
Fixed-line transit schedules	CARTA, WeGO	Static	Chattanooga and Nashville region	Scheduled trips and trip times, routes, stops	General Transit Feed Specification (GTFS)
Video Feeds	CARTA	30 Frames/Second	All fixed-line vehicles	Video frames	Image
APC Ridership	CARTA , WeGO	Every Stop	All fixed-line vehicles	Passenger boarding count per stop	Transit authority specific
Paratransit trips	CARTA	6 months of batch exports	Chattanooga area	Pickup and dropoff locations, timestamps	Transit agency specific

Therefore, we developed a data architecture and processing framework as shown in Figure II.1.13.8. Real-time streaming sensor, static and batch exported data is stored in a MongoDB database deployed on AWS. Datasets are merged and exported for offline model training that is used by downstream optimization applications. Lastly, we include a set of web applications and dashboards for operations teams to use our scheduling and optimization applications as well as monitor their vehicle fleets.

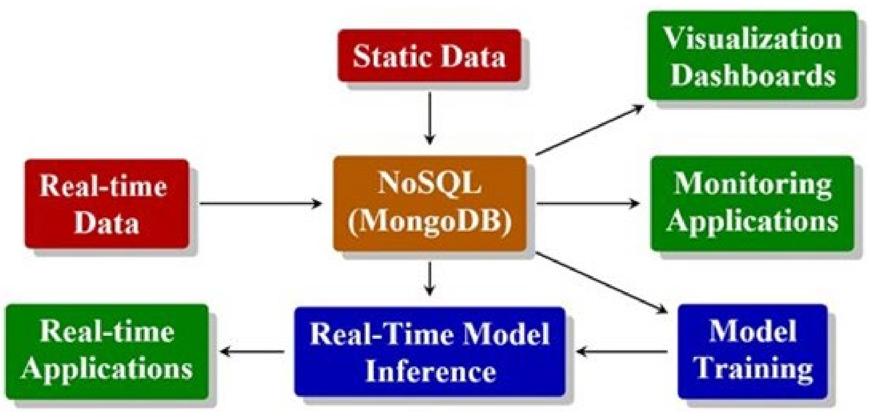


Figure II.1.13.8 Data architecture overview—real time data is streamed to a MongoDB cluster running in AWS with spatial indexing for monitoring and dashboard applications.

An example of this workflow is our work with paratransit dispatch optimization, described earlier. In this case we are working on a web application for operators to take paratransit requests. This application is connected to the MongoDB backend and uses the real-time locations of paratransit vehicles (obtained from GPS readings) as well as current traffic and network conditions to help operators assign new trip requests to vehicles that can service the request. The scheduling algorithms and techniques from our research underpin the assignment model and are made available to the application through APIs. The same workflow applies to energy optimization in which a scheduler uses our energy prediction models to assign buses to fixed-line trips in a way that minimizes energy consumed [2], [9].

Conclusions

Enhancing public transit competitiveness is especially critical in mid-sized cities that are 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 not only energy efficient but will be able to support a larger percentage of the population, improving their transportation choice through enhanced access to transit. The project provides mechanisms to improve transit accessibility with a projected increase from 41% to 73% of residents in the planned study areas while optimizing the energy efficiency of the mixed fleet operations. This will reduce single-occupancy vehicle trips by those residents, significantly decreasing transportation energy use at the city level.

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