

Energy Efficient Mobility Systems

2017 Annual Progress Report

Vehicle Technologies Office

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Acronyms and Abbreviations

A

AADT	Average Annual Daily Traffic
AC	Alternating Current
ACC	Adaptive Cruise Control
accel	Acceleration
ACS	Advanced Combustion Systems
AEO	Annual Energy Outlook
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
ATW	Active Transmission Warm up
AVTE	Advanced Vehicle Testing and Evaluation

B

BaSc	Baseline and Scenario
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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
CBD	Central Business District
CCS	Combined Charging System
CW, CCW	Clockwise, Counter Clockwise
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
CO2	Carbon Dioxide
COMM	Commuter
Conv	Conventional Vehicle
COP	Coefficient of Performance
CPT	Cumulative prospect theory
CRADA	Cooperative Research and Development Agreement
CS	Charge Sustaining
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
EC	European Commission
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

F	Force
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
FLNA	Frito-Lay North America
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
GHG	Greenhouse Gas
GITT	Grid Interaction Tech Team
GM	General Motors
GMLC	Grid Modernization Lab Consortium
GnPs	Graphene nanoplatelets
GO	Graphene Oxide
GPRA	Government Performance and Results Act
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

h-APU hybrid Auxiliary Power Unit

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
IHX	Internal Heat Exchanger
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
LTC	Lockport Technical Center
LV	Leading Vehicle
 M	
M	Mass
MaaS	Mobility as a Service
MBSE	Model Based System Engineering
MD	Medium Duty
MDCEV	Multiple Discrete-Continuous Extreme Value
MDS	Mobility Decision Science
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
MORPC	Mid-Ohio Regional Planning Commission
MOSFET	Metal-Oxide Semiconductor Field-Effect Transistor
MNL	Multinomial Logit
mph	Miles per hour

MPGe, MPGe	Miles per gallon equivalent, Miles per gallon gasoline equivalent
MTC	Metropolitan Transportation Commission
MTDC	Medium Truck Duty Cycle
MOVES	Motor Vehicle Emission Simulator
MRF	Moving Reference Frame
MURECP	Medium-Duty Urban Range Extended Connected Powertrain
MY	Model year
M2	Meters squared

N

NACFE	North American Council for Freight Efficiency
NDA	Non-Disclosure Agreement
NETL	National Energy Technology Laboratory
NHTS	National Household Travel Survey
NHTSA	National Highway Transportation Safety Administration
NM	Newton meters
NO _x	Nitrogen oxides
NR	Natural Rubber
NRE	Non Recurring Engineering
NREL	National Renewable Energy Laboratory
NRT	National Retail Trucking
NVH	Noise, vibration, and harshness
NVUSD	Napa Valley Unified School District
NYSERDA	New York State Energy Research Development Authority

O

OBC	On-board charger
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OCBC	Orange County Bus Cycle
OEM	Original Equipment Manufacturer
OneSAF	One Semi-Automated Forces
ORNL	Oak Ridge National Laboratories

P

P	Active Power
PC	Polycarbonate
PCM	Phase-Change Material
PCU	Power Control Unit
PCU	Powertrain Control Unit
PEEM	Power Electronics and Electric Motor
PEV	Plug-In Electric Vehicle
PFC	Power factor correction
PFI	Port fuel injection
PGW	Pittsburgh Glass Works
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
PMP	Pontryagin Minimum Principle
PMT	Passenger Miles Traveled
ppm	Parts per Million
PTC	Positive Temperature Coefficient (Electric Heater)
PTO	Power Take-Off

PVP	Polyvinylpyrrolidone
PWWMD	Public Works and Waste Management Department
λ	Power Factor
φ	Power Angle
Q	
Q	Reactive power
QA	Quality assurance
QC	Quality control
R	
R ²	Coefficient of Determination
R/D	Receiver / Dryer
REV	New York State's Reforming the Energy Vision Initiative
REx	Range Extending Engine
rGO	reduced graphene oxide
RH	Relative Humidity
RMS	Root Mean Square
ROL	Ring-On-Liner
rpm	Revolutions Per Minute
RSU	Road Side Unit
RTRP-HOPT	Random-Thresholds, Random-Parameters Hierarchical Ordered Probit
RWDC	Real-World Drive-Cycle
S	
S	Apparent power
SAE	Society of Automotive Engineers

SBR	Styrene-Butadiene Rubber
SC03	SC03 Supplemental Federal Test Procedure
SCAG	Southern California Association of Governments
SCAQMD	South Coast Air Quality Management District
SCIG	Southern California International Gateway
SCR	Silicon Controlled Rectifier
SCR	Selective Catalytic Reduction
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
STELLA	Strongly-TypEd, Lisp-like LAnguage
StAR	Storage-Assisted Recharging
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
TSDC	Transportation Secure Data Center
TSI	Turbocharged stratified injection
TUSD	Torrance Unified School District
TV	Trailing Vehicle
TXVs	Thermal Expansion Valves

U

U.S. DRIVE	U.S. Driving Research and Innovation for Vehicle Efficiency and Energy Sustainability
UA	Transfer Coefficient
UC	Ultra-capacitor
UCR	University of California, Riverside

UDDS	Urban Dynamometer Driving Schedule
UM	University of Michigan
UN ECE	United Nations Economic Council for Europe
UNSW	University of New South Wales
UPS	United Parcel Service
URL	Uniform Resource Locator
US06	Environmental Protection Agency US06 or Supplemental Federal Test Procedure
USABC	United States Advanced Battery Consortium
USCAR	U.S. Council for Automotive Research
Util	Battery capacity utilization

V

V	Voltage
V2G	Vehicle-to-Grid
V2I	Vehicle-to-Infrastructure
V2V	Vehicle to Vehicle
VAr	Volt-Amp-reactive
VCC	Volvo Car Corp
VGI	Vehicle-Grid Integration
VGT	Variable Geometry Turbocharger
VHT	Vehicle hours traveled
VIP	Vacuum insulated panels
VKT	Vehicle kilometers traveled
VMT	Vehicle miles traveled
VOTT	Value-of-travel-time
VS	Vehicle Systems
VSATT	Vehicle Systems Analysis Technical Team

VSI	Vehicle Systems Integration
VSST	Vehicle Systems Simulation and Testing
VTCab	Vehicle Thermal Cab Simulator
VTIF	Vehicle Testing and Integration Facility
VTO	Vehicle Technologies Office

W

Dw	Change in Angle W
WCC	Water Cooled Condenser
WEC	World Endurance Championship
WEG	Water/Ethylene Glycol
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
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Y**Z**

ZI-HOPIT	Zero-Inflated Hierarchical Ordered Probit
ZOV	Zero-occupancy vehicle

Executive Summary

Our transportation system is changing. New, disruptive technologies such as connected and automated vehicles are being developed and will soon be 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. This shifting mobility landscape may offer 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.

During fiscal year 2017 (FY 2017), the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) created the Energy Efficient Mobility Systems (EEMS) Program to understand the range of mobility futures that could result from these disruptive technologies and services, and to create solutions that improve *mobility energy productivity*, or the value derived from the transportation system per unit of energy consumed. Increases in mobility energy productivity result from improvements in the quality or output of the transportation system, and/or reductions in the energy used for transportation.

EEMS Program activities during FY 2017 focused on analytical research 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 development of vehicle and transportation system simulation 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.

This document presents a brief overview of the EEMS Program and documents progress and results for projects within three of the five EEMS activity areas: (1) the SMART (Systems and Modeling for Accelerated Research in Transportation) Mobility Lab Consortium (co-managed with VTO's Analysis Program in FY2017), (2) Core Modeling, Simulation, and Evaluation, and (3) Advanced R&D Projects conducted by industry and academia. Some projects within the Advanced R&D portfolio were initiated late in 2017 and therefore are not included in this Annual Report. Similarly, the remaining EEMS activity areas – (4) High Performance Computing and Big Data Solutions for Mobility, and (5) Living Labs (managed under VTO's Technology Integration Program) – were created late in the year, and will be included in the next Annual Report. Each of the individual progress reports provide a project overview and highlights of the technical results.

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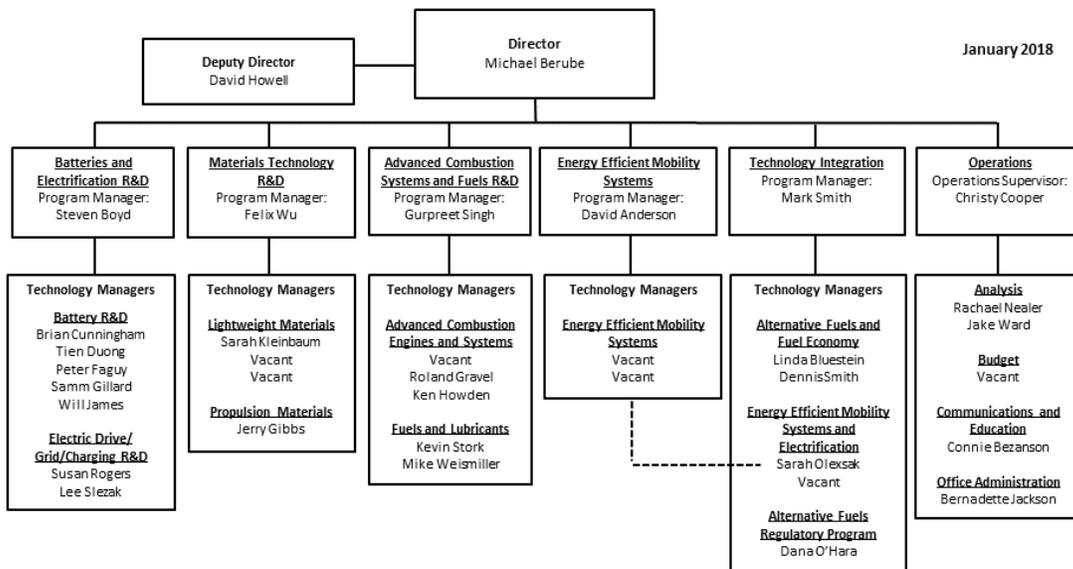
Vehicle Technologies Office Overview

Vehicles move our nation. Vehicles transport more than \$36 billion worth of goods each day¹ and move people more than 3 trillion vehicle-miles each year². Growing our national economy requires transportation and transportation requires energy. The average U.S. household spends nearly one-fifth of its total family expenditures on transportation³, making transportation the most expensive consumer spending category after housing. The transportation sector accounts for 70% of U.S. petroleum use. The United States imports 25% of the petroleum consumed – sending more than \$10 billion per month⁴ overseas for crude oil.

To strengthen national security, enable future economic growth, and increase transportation energy efficiency, the Vehicle Technologies Office (VTO) funds early-stage, high-risk research on innovative vehicle and transportation technologies. VTO leverages the unique capabilities and world-class expertise of the national laboratory system to develop innovations in electrification, advanced combustion engines and fuels, advanced materials, and energy efficient mobility systems.

VTO is uniquely positioned to address early-stage challenges due to strategic public-private research partnerships with industry (e.g., U.S. DRIVE, 21st Century Truck Partnership). These partnerships leverage relevant expertise to prevent duplication of effort, focus DOE research on critical R&D barriers, and accelerate progress. VTO focuses on research that industry does not have the technical capability to undertake on its own, usually due to a high degree of scientific or technical uncertainty, or it is too far from market realization to merit industry resources. VTO’s research generates knowledge that industry can advance to deploy innovative energy technologies to support affordable, secure, and efficient transportation systems across America.

Vehicle Technologies Office Organization Chart



¹ <https://ops.fhwa.dot.gov/publications/fhwahop16083/ch1.htm#t1>

² <https://www.fhwa.dot.gov/policyinformation/statistics/2015/vml.cfm>

³ <https://www.bls.gov/cex/2015/standard/multiyr.pdf>

⁴ Transportation Energy Data Book Edition 34, ORNL, Table 1.7 and Table 10.3; Overseas includes countries and territories outside the 50 States and the District of Columbia.

EEMS Program Overview

Introduction

On behalf of the Vehicle Technologies Office (VTO) of the U.S. Department of Energy (DOE), the Energy Efficient Mobility Systems (EEMS) Program is pleased to submit this Annual Progress Report (APR) for Fiscal Year (FY) 2017.

The emergence of disruptive technologies and services, such as connected and automated vehicles, car-sharing, and ride-hailing services, provide new, low-cost mobility options for consumers. Traditional market players and their business models are facing increased competition from new entrants to the market. This shifting landscape presents a significant opportunity to improve economic and energy productivity and advance safety, affordability, and accessibility in the transportation sector.

While these changes in the transportation system can provide benefits to the American public, they also present risks and challenges that must be addressed. DOE conducts research to understand how this transformation will affect transportation energy consumption and identifies opportunities to create more efficient, affordable, reliable, and secure transportation options that enhance mobility for individuals and businesses. Within DOE's Office of Energy Efficiency and Renewable Energy (EERE), the EEMS Program is responsible for this research portfolio.

This APR describes work that the EEMS Program conducted during FY 2017 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 early-stage research and development (R&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. 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.

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 five coordinated areas of focus, each with its own set of projects. As indicated in Table 1, each of these five activity areas directly supports at least one of the three EEMS strategic goals, and indirectly supports the others. The five activity areas are:

- Systems & Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium
- High-Performance Computing & Big Data Solutions for Mobility
- Advanced R&D Projects
- Living Laboratories
- Core Modeling, Simulation, and Evaluation

SMART Mobility Consortium

The SMART Mobility Consortium is a multi-year, multi-laboratory collaborative dedicated to further understanding the energy implications and opportunities of advanced mobility solutions. The effort consists of five pillars of research:

1. **Connected and Automated Vehicles (CAVs):** Understanding the energy, technology, and usage implications of connected and autonomous technologies and identifying efficient CAV solutions.
2. **Mobility Decision Science (MDS):** Identifying the transportation energy impacts of potential travel and lifestyle decisions and understanding the human role in the mobility system.
3. **Multi-Modal Transport (MMT):** Reducing modality interface barriers for passenger and freight movement and understanding the interrelationships between various modes.
4. **Urban Science (US):** Evaluating the intersection of transportation networks and the built environment in terms of energy opportunities.
5. **Advanced Fueling Infrastructure (AFI):** Understanding the costs, benefits, and requirements for fueling/charging infrastructure to support energy efficient future mobility systems.

The SMART Mobility Consortium supports EEMS Strategic Goal #1 as the 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 directly supports Strategic Goal #2 by identifying R&D gaps that the EEMS Program may address through its advanced research portfolio. The SMART Mobility Consortium will also generate insights that will be shared with mobility stakeholders, indirectly supporting Strategic Goal #3.

High Performance Computing and Big Data Solutions for Mobility

The EEMS Program uses the national laboratories' capabilities in high performance computing (HPC) and big data analytics to research the application of artificial intelligence (AI) techniques such as machine/deep learning and data science tools. These efforts assist in the design, planning, and operation of future mobility systems. 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 (physical) data and human decision-making (behavioral) data.

The EEMS Program develops and applies the national laboratories' HPC expertise, machine learning, and big data science to find solutions to real-world transportation energy challenges. The program's initial efforts in this area are:

The HPC4Mobilitys initiative establishes small seedling projects that partner national lab capabilities with third parties who have access to data.

The Big Data Solutions for Mobility initiative supports the national laboratories to develop the scalable data science and HPC-supported computational framework needed to build next-generation transportation/mobility system models and operational analytics.

HPC4Mobility and Big Data Solutions for Mobility initiatives merge exploratory findings of the SMART Mobility Consortium, specific data sets from public and private entities, and unparalleled computational and analytical resources. These resources will solve specific transportation energy challenges faced by cities, states, and regions across the United States, such as how 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 Strategic Goals #1 and #2. This activity indirectly supports Strategic Goal #3, as it involves collaboration with stakeholders in the mobility ecosystem to be successful.

Advanced R&D Projects

The EEMS Program's Advanced R&D activities focus on innovative, early-stage, and scalable mobility projects and target system-level opportunities to reduce the energy intensity of the movement of people and goods. The program partners with industry and academia to research and develop technology solutions that lead to energy savings through advancements in hardware, software, control systems, advanced sensors, 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 technology companies 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 enormous 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 R&D project portfolio directly supports Strategic Goal #2 by developing innovative technology solutions for mobility. This activity indirectly supports Strategic Goals #1 and #3 since the results from these R&D efforts feed into the analytical work to understand the impacts of these new technologies, and are disseminated to the stakeholder community.

Living Laboratories

EEMS Living Laboratories, led by VTO's Technology Integration Program, works with cities and stakeholders to demonstrate and evaluate new mobility technologies in the field and collect data. These projects are an important feedback mechanism to R&D and provide a source of real-world data to test, validate, and improve models, simulations, software, and hardware. The EEMS Program coordinates and collaborates with stakeholders to support city and regional efforts to develop energy efficient transportation systems through key elements of an implementation strategy: stakeholder engagement, Living Laboratory projects, and technical assistance.

As the primary insight sharing and stakeholder collaboration element of the EEMS Program, Living Laboratories directly supports Strategic Goal #3. Additionally, the data collected through the Living Labs activity is important to the analytical and R&D efforts and indirectly supports Strategic Goals #1 and #2.

Core Modeling, Simulation, and Evaluation

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 lab 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. These capabilities are critical to the EEMS Program in evaluating the energy and mobility outcomes of future

transportation systems, and 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 tools is critical to the EEMS Program’s ability to understand the impacts of future mobility and directly supports Strategic Goal #1. The tool set is also important in identifying research opportunities and producing insights to share with mobility stakeholders and indirectly supports Strategic Goals #2 and #3.

The table below shows how the EEMS activities align with the EEMS strategic goals.

Table 1 - Alignment of EEMS Activities with Strategic Goals

EEMS STRATEGIC ALIGNMENT			
LEGEND	Goal 1: Tools, Techniques, & Capabilities to Understand & Improve Mobility Energy Productivity	Goal 2: Early Stage R&D to Develop Innovative Technology Solutions for Efficient Future Mobility Systems	Goal 3: Insight Sharing, Stakeholder Coordination and Collaboration on Local & Regional Transportation Systems
● = Activity Directly Supports Goal			
▲ = Activity Indirectly Supports Goal			
SMART Mobility	●	●	▲
HPC/Big Data Analytics	●	●	▲
Advanced R&D	▲	●	▲
Living Laboratories	▲	▲	●
Core VTO Tools	●	▲	▲

Coordination

The EEMS program coordinates its activities with the U.S. Department of Transportation (DOT) and Industry. The coordination with the U.S. DOT is based on the following objectives

- Gain mutual benefit from coordination between DOT’s Smart City Challenge and VTO’s SMART Mobility Lab Consortium.
- Provide leadership and best practices in the development and analysis of transportation data management.
- Leverage each agency’s technical expertise and previous experience in mobility related technologies.
- Utilize and share existing stakeholder networks for institutional knowledge of local resources.
- Support a Technologist-in-Cities pilot, embedding a mobility energy expert within a Smart City:

In addition to intergovernmental collaboration with DOT, the EEMS Program coordinates with industry partners. For example, U.S. DRIVE (“Driving Research and Innovation for Vehicle efficiency and Energy sustainability”) is a non-binding and voluntary government-industry partnership focused on advanced automotive and related energy infrastructure technology research and development.⁶ In 2017, U.S. DRIVE created an EEMS Working Group to explore topics of mutual interest to U.S. DRIVE members. The working group prioritized analyses of infrastructure technologies and VMT (vehicle miles travelled) effects of new mobility solutions.

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.

For FY 2017, the SMART Mobility activities were co-funded by the VTO Analysis team and VTO’s EEMS Program. Several of the SMART Mobility project reports appear in both the Analysis FY 2017 APR and the EEMS FY 2017 APR.

The VTO Technology Integration Program funded and has primary management responsibility for Living Laboratories projects during FY 2017. Living Laboratories projects are not included in the FY2017 EEMS APR.

Research Highlights

FY2017 was the first year of the Energy Efficient Mobility Systems Program, and the research activities conducted were primarily analytical in nature. The SMART Mobility Lab Consortium produced many research findings and insights about the energy and mobility impacts of new transportation technologies and services. These insights are described in detail through the remainder of this Annual Progress Report. Selected highlights and accomplishments from these activities are summarized here.

- Through the SMART Mobility Advanced Fueling Infrastructure pillar, the Idaho National Lab (INL) led work with the National Renewable Energy Lab (NREL) and Argonne National Lab (ANL) to develop and utilize a framework to estimate the potential DC Fast Charging requirements for an EV ride-hailing service in Columbus, Ohio. Installation and operating costs were estimated using real-world data to evaluate the economic feasibility of the charging infrastructure for which optimized locations were produced using the EVI-Pro model. (*AFI Pillar Task 2.1, Analysis of Fast Charging. Services Station Network for Electrified Rid-Hailing*)

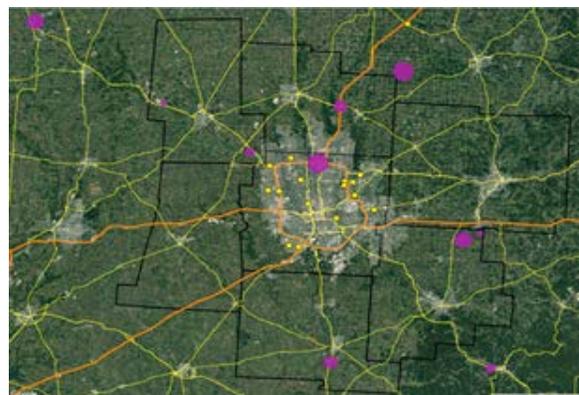


Figure I.1-1 - DCFC location hot spots to support ride-hailing vehicles and existing stations in the Columbus region

- ANL enhanced its agent-based transportation system model POLARIS to simulate the impact of various connected and automated vehicle (CAV) technology scenarios, to evaluate the impact of CAVs on traffic flow and congestion. This sophisticated model incorporates resource allocation to model realistic

behavior such as household vehicle sharing in future mobility scenarios, and has quantified the energy impacts of multiple CAV penetration cases based on behavioral assumptions developed in the Mobility Decision Science pillar. (CAV Pillar Task 7A.1.3, *Impact of Connected and Automated Vehicles on Energy and Mobility in a Metropolitan Area*)

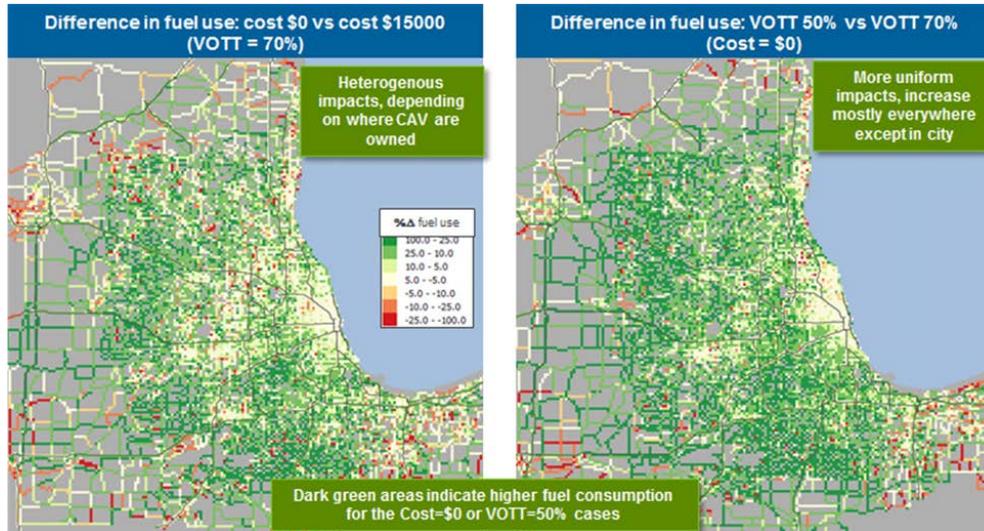


Figure I.1-2 - CAV Scenario Fuel Use Changes

- The CAVs pillar also produced previously unavailable experimental data demonstrating the energy savings that could be achieved through cooperative automation of heavy-duty trucks by developing a cooperative adaptive cruise control (CACC) system to tightly couple three trucks into a platoon. The results of this project, led by Lawrence Berkeley National Lab (LBNL) with support from NREL, showed that fuel consumption could be reduced by up to 13% for the entire platoon, while also providing new insights about the impact of speed, vehicle separation, and real-world mixed traffic on the fuel savings. (CAV Pillar Task 7A.3.1, *Truck CACC/Platooning Testing: Measuring Energy Savings, Interaction with Aerodynamics Changes and Impact of Control Enhancements*)



Figure I.1-3 - Picture of platooning test in Blainville, Quebec

- LBNL successfully enhanced the BEAM/MATSim simulation platform to achieve scalable, dynamic transportation system simulation capabilities that include all modes of travel, and have applied it to the San Francisco Bay metropolitan area. As part of this task within the Mobility Decision Science pillar, LBNL, in collaboration with ORNL, modeled the spatio-temporal energy consumption of the San

Francisco area transportation system by mode and by fuel, and demonstrated the impact that behavioral decisions (such as changes in mode choice induced by changes in cost, for example) have on this energy consumption. *(MDS Pillar Task 3.1, Travel Behavior Simulation Modeling – MATSim / BEAM)*

- NREL and LBNL collaborated under the Mobility Decision Science pillar to analyze the relationship between transportation network companies (TNCs) and vehicle registrations. This is an important step in understanding the potentially dramatic impacts that new mobility services will have on vehicle miles traveled (VMT) and transportation energy use. *(MDS Task 2.2, TNC Services Impacts on Travel Behavior and Energy Use)*
- Under the Multi-Modal Transportation pillar, Oak Ridge National Lab (ORNL), NREL, and INL coordinated to evaluate opportunities to improve the cost and efficiency of last-mile freight delivery. The team has developed several novel freight delivery models, data techniques, and analytical approaches. As new freight delivery technologies and services become available in response to e-commerce-based consumer demand, it is critical that these modes be understood in the context of the transportation system. *(MM Pillar Task 3.1, Optimization of Intra-City Freight Movement and New Delivery Methods)*

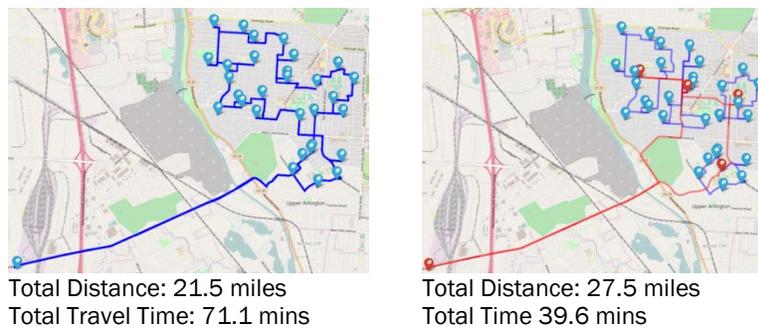


Figure I.1-4 - Example delivery model changes from traditional to hub-based delivery

- The Multi-Modal Transportation pillar has also investigated long-haul, inter-city freight, quantifying the national-level energy impacts of opportunities to optimize freight movement through new technologies and mode-shifting. The results of this task indicate that up to 5,330 Trillion BTUs could be saved cumulatively from 2016 to 2040 due to opportunities to leverage truck platooning at the national scale. ANL, NREL, and NREL demonstrated that this reduction could be over 4% of the annual energy consumed in the freight sector. *(MM Pillar Task 2.1, National Scale Multi-Modal Energy Analysis of Inter-City Freight)*

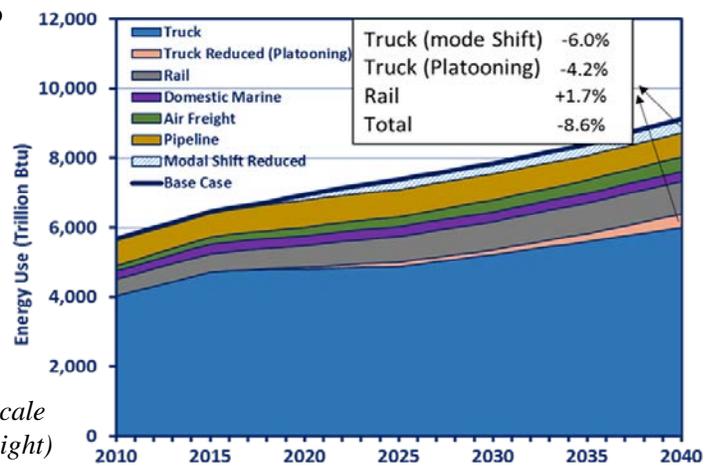


Figure I.1-5 - Freight sector total energy reduction due to platooning and mode shift

- The Urban Science pillar, through efforts led by NREL and INL, have evaluated the current state of urban data and mobility models used by cities in their transportation planning. The team has found that there is a potential gap in the ability for many cities to adequately plan as new mobility technologies and services emerge, due to limitations in data and modeling capabilities. It is critical that metropolitan planning organizations (MPOs) and other

transportation planning officials be able to consider the impacts of automation, connectivity, electric transportation, and shared mobility services as they make infrastructure investments that will persist for decades. (*US Pillar Task 2.1 & 2.2, Mobility Data & Models Informing Smart Cities for Urban Travel, Land Use, and Infrastructure Transitions*)

I am pleased to submit the first Annual Progress Report for Energy Efficient Mobility Systems for FY 2017. Inquiries regarding the EEMS Program and its research activities may be directed to the undersigned.

A handwritten signature in black ink that reads "David L. Anderson". The signature is written in a cursive, flowing style.

David L. Anderson
Program Manager

I. SMART Mobility – Advanced Fueling Infrastructure (AFI)

I.1 National energy impacts of electrification infrastructure deployment for shared mobility-near-term benefit estimation [Task 1.1]

Yan Zhou, Principal Investigator

Argonne National Laboratory
9700 S Cass Avenue
Lemont, IL 60439
Phone: (630) 252-1215
E-mail: yzhou@anl.gov

Eleftheria Kontou, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-4782
E-mail: Ria.Kontou@nrel.gov

Fei Xie, Principal Investigator

Oak Ridge National Laboratory
2360 Cherahala Boulevard
Knoxville TN 37932
Phone: (865) 946-1306
E-mail: xief@ornl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2017

Total Project Cost: \$250,000

DOE share: \$250,000

Non-DOE share: \$0

Project Introduction

Infrastructure has long been a major barrier to alternative fuel vehicle (AFV) adoption such as plug-in electric vehicles (PEVs). Cost-effective fueling infrastructure is needed to support energy efficient shared mobility applications. The rapid development and deployment of advanced charging technologies (e.g., DCFC, DWPT), and vehicle connectivity and automation technologies will impact vehicle ownership and use, electricity generation, and alternative fuel production/supply (e.g., hydrogen, biofuel) resulting in major changes in the utilization of alternative transportation modes, energy consumption, and economic activity. Understanding the magnitude and sensitivity of these impacts is key to identifying barriers and achieving mainstream adoption of AFVs. While analysis, modeling and planning activities associated with Tasks 2-4 under AFI pillar will identify deployment pathways for advanced charging at the regional level for different vehicle types and road types, the synthesis of the many specific cases proposed under Task 1 is critical to understanding national level impacts for the range of pathways and identifying particularly beneficial options. However, there is very limited understanding on energy impacts of shared mobility applications with electrification infrastructure support.

Objectives

The objective is to assess the national energy and economic benefits based on regional simulation results of deploying electrification infrastructure to support shared mobility. FY 2017 focus on near term, intra-city charging infrastructure for shared vehicles without full automation

Approach

This task relies on regional infrastructure modeling from Task 2 of AFI pillar. Aiding the objectives of Task 1, particularly in terms of estimating national energy and emission impacts of near term electric vehicle charging infrastructure for both inter- and intra-city traveling, Task 2 methods are supporting both goals by looking into infrastructure needs in smaller regions (e.g., city of Columbus, Ohio) for shared mobility systems. The goal of this task interaction is to aggregate regional impacts of Transportation Network Companies (TNC) operation, such as ride-hailing effects on vehicle miles traveled (VMT) and percentage on eVMT increase, and extrapolate them on a national level.

After identifying the appropriate metrics, such as VMT impacts of TNC by population density, trip type, and class, the outcomes of the regional analysis can be utilized to generalize national level outputs by following the process, shown in Figure I.1-1. More importantly, the infrastructure availabilities from regional simulation then will be translated to charging opportunities defined for urban and rural area for each state. In the same time, literature review is conducted to assess the survival rates and VMT per vintage of TNC vehicles. The impact of TNC deployment on private passenger vehicle ownership at regional level is also summarized from limited literature.

To evaluate impacts of urban public charging on the near-term BEV adoption, in FY 2017 we consider three scenarios defined based on different assumptions on the charging infrastructure in the near-term planning horizon (2011-2025). In particular, the “NoAFI” scenario (AFI represents advanced fueling infrastructure) is a pessimistic one which assumes very limited infrastructure level in the entire national scale (5% opportunity and 3 KW average charging power in urban area throughout the time horizon for all states). The “AFI_Base” scenario recognizes the recent development in infrastructure up to 2017 (as shown in Figure I.1-2), while this scenario assumes that the 2017 infrastructure level remain the same in the rest of years. The “AFI_Double” scenario is identical to the “AFI_Base” scenario between 2011-2017. After 2017, the “AFI_Double” scenario recognizes a moderate increase in the charging deployment with a deployment level reaches twice the 2017 level in 2025. Note that all the three scenarios assume that there are scarce charging infrastructure support in the rural area in all years (charging opportunity = 5% and charging power = 3KW).

This study utilizes national labs’ sophisticated tools (VISION, EVI-Pro, MA3T, etc.), database (Transportation Secure Data Center, EV Project), and expertise to identify solutions that overcome barriers to future sustainable transportation. VISION is a model developed by Argonne National Laboratory to provide estimates of the potential energy use, oil use and carbon emission impacts of advanced light- and heavy-duty vehicle technologies and alternative fuels through the year 2100. EVI-Pro, Electric Vehicle Infrastructure Projection Tool (EVI-Pro), is a model developed by National Renewable National Laboratory to estimate future requirements for charging infrastructure. MA3T, Market Acceptance of Advanced Automotive Technologies model developed by the Oak Ridge National Laboratory. The core of the model is a nested multinomial logit model that simulates purchase probability of advanced vehicle technologies of 9,180 consumer segments, representing the U.S. vehicle market. To represent the evolving market environment, the MA3T model takes exogenous inputs on technology, policy, consumers, and infrastructure. In particular, public charging factors are part of the infrastructure input.

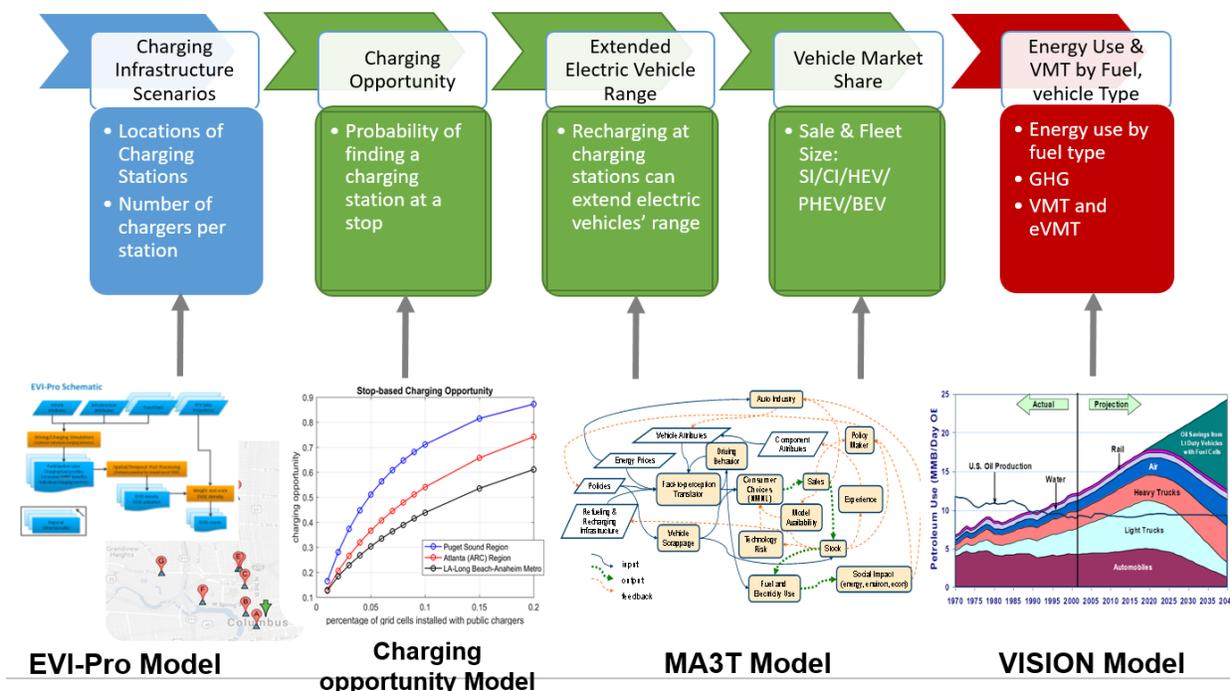


Figure I.1-1 - Approach for analyzing infrastructure impacts on shared plug-in electric vehicle market share and energy use

Results

The ride hailing trip data emulation was applied to 5,000 passenger days from personal GPS data from Columbus Ohio. Results suggest a decrease in the number of vehicles needed to accommodate the same number of trips, and increase of the total number of trips on the network due to deadheading, a 3.5 % increase in VMT, and the mean of daily VMT increase by 29% and the average trip's distance decreases by 24%.

The outputs of the EVI-Pro showcase differences between infrastructure needs for personal cars operation and TNC cars operation. Results suggest that residential charging requirements remain similar for personal and ride-hailing vehicles; the demand for non-residential charging is drastically different. More frequent public events are observed in public locations combined with higher daily VMT increases the need for public L2 and DCFC by 83% and 82% respectively.

Figure I.1-2 shows the BEV market share in 2025 sales in both urban and rural areas for the three scenarios. It is shown that the BEV market share increases significantly for both AFI scenarios compared to the NoAFI scenario. Compared to the NoAFI scenario, the AFI_Base scenario increase the market share from 15% to 18.2%, while doubling the availability in 2025 will further increase the share to 19.4% level. Major increase in the share occurs in the urban area as we assume that the charging infrastructure is expanded only in the urban area.

BEV market share in rural area is slightly higher than in urban area for the NoAFI scenario. Note that the rural area has more shares of single-family home (U.S. Census Bureau, 2011) and thus we assume that there are more home charging availability in the rural area. Therefore in the NoAFI scenario, when both urban and rural areas have scarce public charging infrastructure, consumers in rural areas are more likely to accept BEVs. On the other hand, the other two AFI scenarios do invert this condition, mainly thanks to the significant development in the urban public charging.

Compared to the NoAFI scenario, Figure I.1-3 shows the relative changes (Figure I.1-3 (b)) in the BEV sales comparing with NoAFI scenario. According to Figure I.1-3(a), the relative change in BEV sales peak in 2017

at 30% level. After 2017, the relative changes for the two scenarios are decreasing. For the AFI base scenario, we assume there is no change in the existing charging infrastructure. This AFI base assumption reduces the infrastructure impact on the sale significantly while other factors still increase benefits for the BEV sales (e.g., reduction in battery cost). For the AFI Double scenario, though it considers further expansion in the infrastructure, the expansion is still moderate, and that also contributes to the relative reduction.

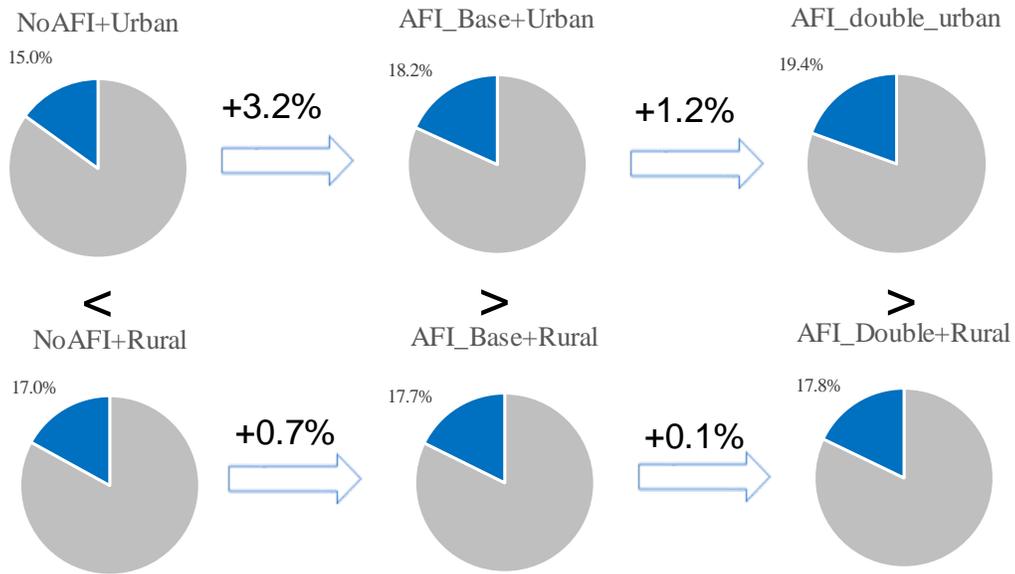


Figure I.1-2 - 2025 BEV market share in urban and rural areas (blue area represents the BEV market share)

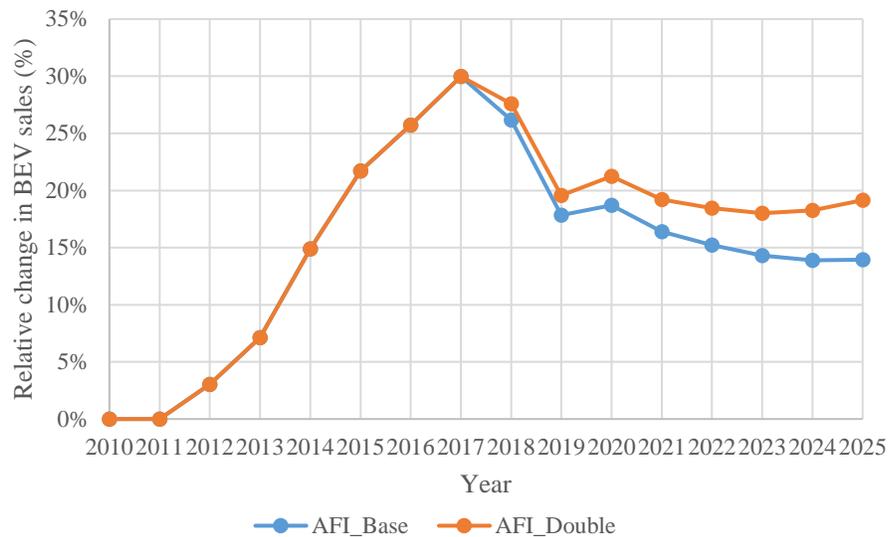


Figure I.1-3 - Change in BEV total sales relative to NoAFI scenario

Conclusions

Regional simulation results suggest that residential charging requirements remain similar for personal and ride-hailing vehicles; the demand for non-residential charging is drastically different. More frequent public events are observed in public locations combined with higher daily VMT increases the need for public L2 and DCFC. We also found that the development in recent charging infrastructure successfully stimulates the recent BEV market and additional investment on the infrastructure will further increase the adoption for TNC vehicles.

As this study only focused on the impacts of public charging infrastructure in urban areas because our literature review shows that TNC will likely be more popular in population dense areas. Further investigation on future rural infrastructure is an important addition to understand their benefits in covering long-distance or inter-city travels of BEVs.

Next step, due by Q1FY 2018, we will estimate national energy impacts of electrification infrastructure supporting TNCs with projected market shares, eVMT%, estimated survival rates and VMT per year.

Key Publications

6. Yan Zhou, Modeling and Analysis of Plug-in Electric Vehicle Charging Infrastructure Supporting Shared Mobility, DOE VTO Annual Merit Review, June, 2017, Washington D.C.
7. Wood, E., Rames, C., Kontou, E., Motoaki, Y., Zhou, Z. and Smart, J. (2018). Analysis of Fast Charging Station Network for Electrified Ride-Hailing Services. Submitted to SAE World Congress 2018.
8. Fei Xie, Zhenhong Lin, Yan Zhou. Near-Term Impacts of Expanding National Public Charging Infrastructure on Electric Vehicle Market Adoption. Presented at Behavioral, Economics, and Climate Change Conference in October 2017.
9. Fei Xie, Zhenhong Lin, Yan Zhou. Impacts of Advanced National Public Charging Infrastructure on Battery Electric Vehicle Market Adoption. Submitted to the 2018 CICTP conference.

I.2 Analysis of Fast Charging Station Network for Electrified Ride-Hailing Services [Task 2.1]

Yutaka Motoaki, Principal Investigator

Idaho National Laboratory
2525 Fremont Avenue
Idaho Falls, ID 83402
Phone: (208) 526-3752
E-mail: yutaka.motoaki@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$1,070,000

End Date: September 30, 2019
DOE share: \$1,070,000

Non-DOE share: \$0

Project Introduction

Today's electric vehicle (EV) owners charge their vehicles mostly at home and seldom utilize public direct current fast charger (DCFCs), reducing the need for a larger deployment of DCFCs for private EV owners. However, due to the emerging interest among transportation network companies (TNCs), whose operation requires quick fueling to operate EVs in their fleet, there is great potential for DCFCs to be highly utilized and become economically feasible in the future as EV ride-hailing business further prevails.

Objectives

The Advanced Fueling Infrastructure Pillar team used simulation to study estimated potential DCFC needs (location, number of plugs, and electricity demanded) by a hypothetical EV ride-hailing service in Columbus, Ohio. Operation cost and installation cost were estimated using real-world data to assess the economic feasibility of DCFCs at the recommended locations.

Approach

The work for this project was performed by staff from INL, NREL, and ANL.

Due to the unavailability of data that describe TNC vehicle movements, a heuristic that emulates TNC vehicle data for ride-hailing systems using as inputs personal trip data sets was deployed. The heuristic process objective is to enable allocating personal trips to TNC vehicle IDs, by essentially grouping together trips that can be conducted consecutively, and by allocating groups to TNC vehicle IDs.

The proposed algorithm, which is portrayed using a schematic representation, first identifies trip candidates that can be conducted consecutively based on the location and time of their destinations and origins. In this step, we created a candidacy list C_i that contains all trips $j \neq i$ whose origin is within a specified space and time distance from a certain trip's i destination (we do that for all trips in the set I where $i, j \in I$) by imposing two constraints: a) the down time between trips is less or equal to an upper bound t^{\wedge} and greater or equal to the required time t_d to cover the distance between the trip's i destination and the next trip's j origin with $t_d = \frac{d_{ij}}{s}$ (note that d_{ij} is the distance between the trip's i destination and the next trip's j origin and s the average speed to cover that distance), b) and the deadheading distance d_{ij} is less than or equal to an upper bound d^{\wedge} . There is no provision that allows customers to wait for TNC vehicles and depart later than the desired time (which is the time of departure as defined in the personal trip data set) since trip origin and destination times are strictly set and are not flexible. This assumption also implies that the trips' times and distances, as well as

routes have not changed or been impacted due to the TNC vehicle operation and are the same as the ones in the personal trip data set.

The second step of the heuristic involves determining which trip j that is included in the candidacy list of i will be conducted in sequence—this process constitutes trip-matching. The trip that belongs to C_i with the minimum deadheading distance ($\min d_{ij}, j \in C_i$) is selected and conducted after i under the assumption that the driver of the TNC automobile or the application that assigns that vehicle to the next trip goal is the minimum of the deadheading distance between the trips in a sequence. Note that the heuristic described above does not assign trips that cannot be grouped with other trips to TNC vehicles IDs due to the time and location constraints set. We assumed that those trips are conducted by a personal vehicle. The heuristic algorithm was implemented in Python 2.7.12 leveraging the processed INRIX data.

This study used the Ohio Power Company – Columbus Southern Power Rate Zone Bill Calculation Spreadsheet to estimate monthly electricity bills (Ohio Power Company 2017). The spreadsheet receives a month-long hourly energy usage profile (kWh) and outputs the approximate monthly bill from that data for each applicable rate plan. An ordinary least-squared regression was estimated to examine the statistical association between total installation cost and the identified cost drivers.

Results

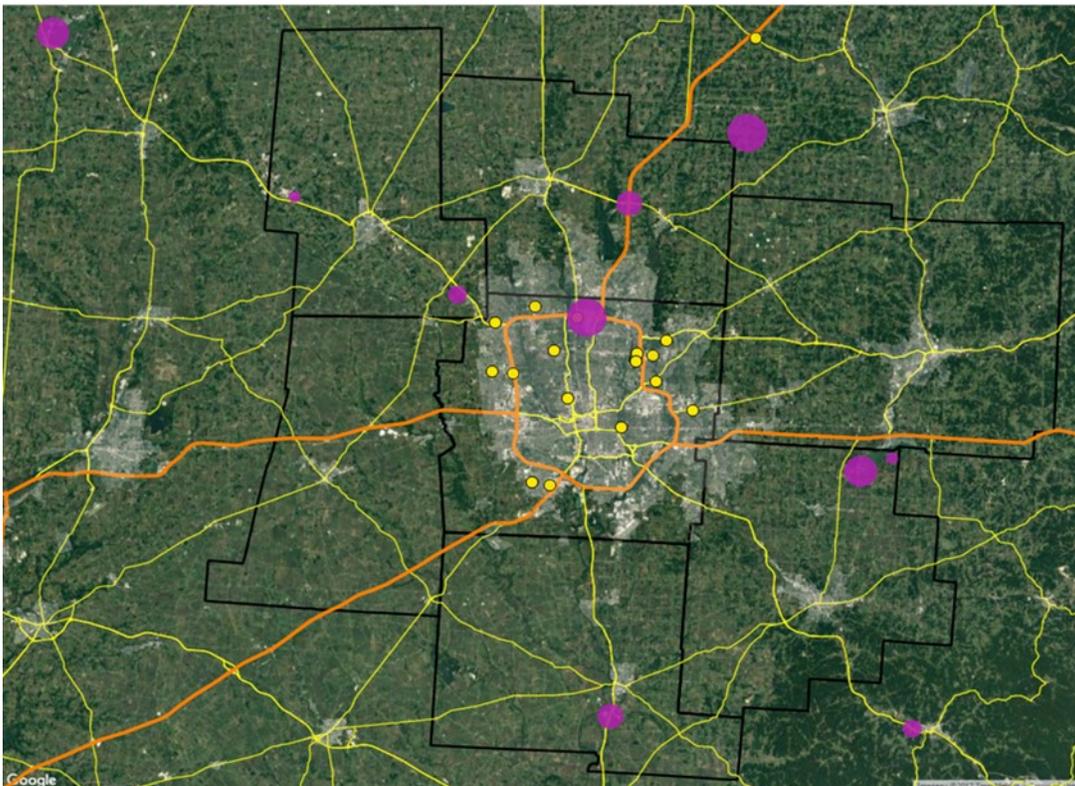


Figure I.2-1 - DCFC location hot spots to support ride-hailing vehicles and existing stations in the Columbus region

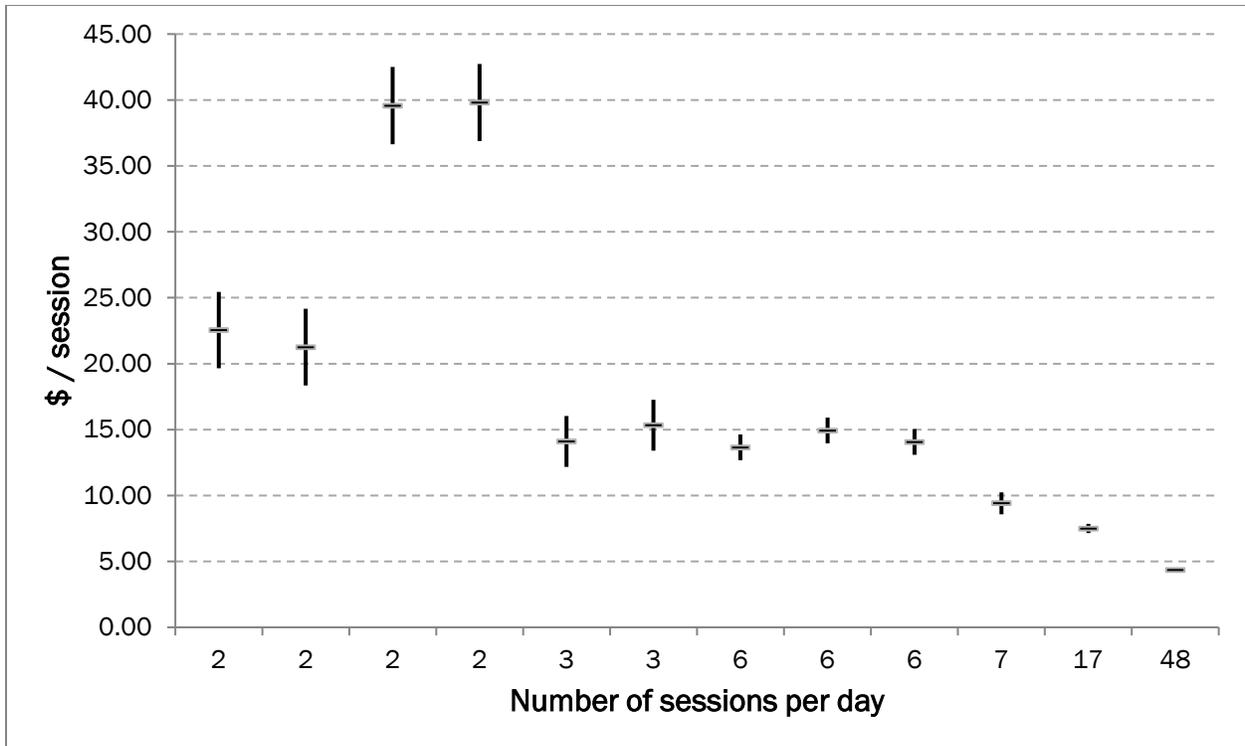


Figure I.2-2 - Total cost per session

Table I.2-1 - Average station utilization metrics (sessions/day)

#charging sessions/day	Personal vehicles	Ride-hailing vehicles
Public L2	2.2	2.1
DCFC	1.0	3.5

Table I.2-2 - Average station utilization metrics (kWh/day)

kWh/day	Personal vehicles	Ride-hailing vehicles
Public L2	16.8	15.4
DCFC	12.8	29.2

Table I.2-3 - Simulated Charging Stations' Monthly Electricity Bill Estimation

Location	No. of Sessions (monthly)	Daily total energy usage (kwh)	Monthly total energy usage (kwh)	Maximum demand (KW)
1	180	117.81	3534.40	82.06
2	510	297.11	8913.42	61.5
3	60	85.24	2557.22	61.5
4	60	91.51	2745.31	61.5
5	180	94.17	2825.13	66.85
6	180	155.66	4669.68	61.5
7	1440	638.35	19150.64	78.91
8	60	17.58	527.32	28.93
9	90	30.75	922.40	28.75
10	60	26.63	922.40	20.5
11	210	52.91	1587.35	33.55
12	90	23.36	700.90	20.5
Average	260	135.92	4077.73	50.50

Table I.2-4 - Cost Model Coefficient estimates

	Coefficient	Standard. Error	P-value	2.5%	97.5%
Intercept	18,290.26	863.02	<0.01	16,574.63	20,005.88
Service Upgrade	4,559.02	1,611.92	<0.01	1,354.61	7,763.41
Underground × Distance	106.69	34.15	<0.01	38.79	174.59
Underground × Gravel	-4,687.10	2,241.56	<0.05	-9,143.19	-231.02
R-squared: 0.204					
Adjusted R-squared: 0.176					

Conclusions

The EVI-Pro model recommended 12 sites for DCFC installations to support a hypothetical PEV ride-hailing service in Columbus, Ohio. A negative relationship between cost per unit of energy usage and the number of charging sessions was found to be caused primarily by the monthly charge and demand charge averaging out with increased energy use from more charging sessions. Among the recommended sites, the sites with overhead service lines are recommended for hosting the DCFC as trenching and boring that are required for underground service line extension can be a considerable cost driver. Although the cost of service upgrade generally is a significant cost driver, all the recommended sites that are within AEP Ohio's territory were found to have enough service capability to support DCFCs. The uncertainty in the actual installation cost may affect the total cost; however, as the level of utilization increases, the operation cost dominates the total cost. Therefore, for DCFC site selection for a ride-hailing service, priority should be placed upon the level of potential utilization.

Key Publications

1. A conference paper describing findings from FY 2017 research, entitled "Analysis of Fast Charging Station Network for Electrified Ride-Hailing Services", was submitted for presentation at SAE World Congress in January, 2018.

I.3 Techno-economic feasibility assessment of High-Power Fast Charging to Support the Electrification of Shared Mobility Fleets [Task 3.1]

Shawn Salisbury, Principal Investigator

Idaho National Laboratory
 P.O. Box 1625
 Idaho Falls, ID 83415
 Phone: (208) 526-3430
 E-mail: shawn.salisbury@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
 Phone: 202-287-5688
 E-mail: David.Anderson@ee.doe.gov

Start Date: October 12, 2016
 Total Project Cost: \$250,000

End Date: April 1, 2018
 DOE share: \$250,000

Non-DOE share: \$0

Project Introduction

In the coming years, it is expected that electric vehicles (EVs) will see increased market penetration, especially in the shared-mobility space. For many drivers who travel a large number of miles, like drivers for shared-mobility fleets, the use of direct current fast charging (DCFC) infrastructure will be necessary. To meet the needs of more customers, many EV models are being offered with larger batteries and greater driving range. Utilizing current fast charging infrastructure, a vehicle with a larger battery will require a longer charge time. For this reason, manufacturers of EVs and DC fast chargers are planning and developing products capable of higher power charging. Current DCFC infrastructure is known to be expensive to install and operate, especially for sites which see low utilization. It is generally accepted that higher power fast charging will bring with it even higher costs.

Objectives

This work investigates the feasibility of using high-power fast charging stations to support the electrification of shared-mobility fleets in terms of cost and customer experience. There are a number of considerations that affect the operation of a fast charging station, including charging port power, the number of ports at a site, the available grid power at that site, and customer usage. Relationships among these and other considerations could yield significant tradeoffs with respect to station capital and operation expenses, user cost for a charge, utilization rates of the station, and the experience or quality of service of its users.

Approach

The work for this project was performed by staff members at INL and NREL. Based upon previous tasks in the SMART Mobility Advanced Fueling Infrastructure (AFI) pillar, it has been determined that in order to support the electrification of shared-mobility vehicles, fast charging infrastructure will be required. In many cases, multiple fast chargers will need to be located at a site to accommodate the demand in a given location.

The power draw during fast charging is highly variable. Generally, charges start with high power, but power will decrease rapidly as batteries approach their maximum state of charge. When multiple vehicles are charging simultaneously at a single site, the power requirement from that site will vary depending on exactly when charges start, how many charges occur at the same time, charging power, and the vehicle's initial state. Based upon these considerations, it was determined that a charging station model must be created to understand the operation of the charging site as a whole.

In addition to the station operation, this task uses a cost model to determine the capital and operating expenses for the studied charging sites. The integrated cost and operation models will allow for comparisons to be made between stations of varying size and usage patterns. The station model will take inputs from AFI tasks which determine the charging needs of future shared-mobility vehicles and develop time-series power curves for the simulated charging sites. From these power curves and the design of the station, capital and operating costs will be estimated for the entire charging station.

This task is a joint effort between Idaho National Laboratory and the National Renewable Energy Laboratory, and is performed in close collaboration with the other members of the SMART Mobility AFI pillar. In FY2017, the focus of this task was mainly on developing a functioning model. The focus in FY 2018 will be on refining the model so it can be used to assess the charging needs for future mobility scenarios developed by the AFI pillar. This will include an investigation on how station sizing, which includes the number of charging ports, the electrical capacity of the station, and the charge power of each port, will impact station costs and customer experiences, such as charging time and wait time.

Results

The architecture of the overall station model can be seen in Figure I.3-1.

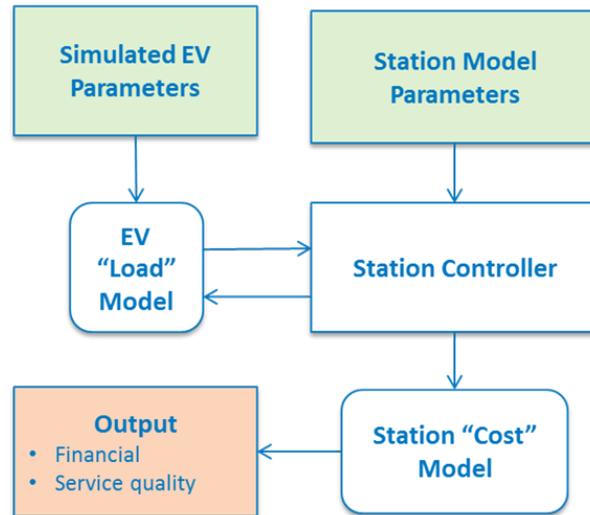


Figure I.3-1 - Overall fast charging station modeling framework

In this modeling framework, the inputs are parameters of the station model design and simulations of EV charging needs. Station model inputs include the rate structure for electricity costs, the number of charging ports, and the electrical capacity of the site. EV parameters come from simulations performed by NREL’s EVI-Pro modeling tool and include outputs such as arrival time, energy needed, and initial vehicle state of charge (SOC). These EV parameters are used by the “load” model and station controller model created by NREL as probability distributions to develop multiple charging event schedules for the station through the Monte-Carlo method. This approach allows for the tool to output probabilistic peak electrical demand, port usage, and queue times for various station model parameters and control strategies. The model develops many finite arrival and energy demand events for a month and then simulates those event schedules through the EV “Load” Model and Station Controller to determine each vehicle’s charging power profile based on the station and other vehicles states.

Included in the EV load model is a “charge acceptance” model which allows charging power to be dynamically limited based upon the vehicle’s state of charge. A sample charge profile which is created using this model is shown in Figure I.3-2.

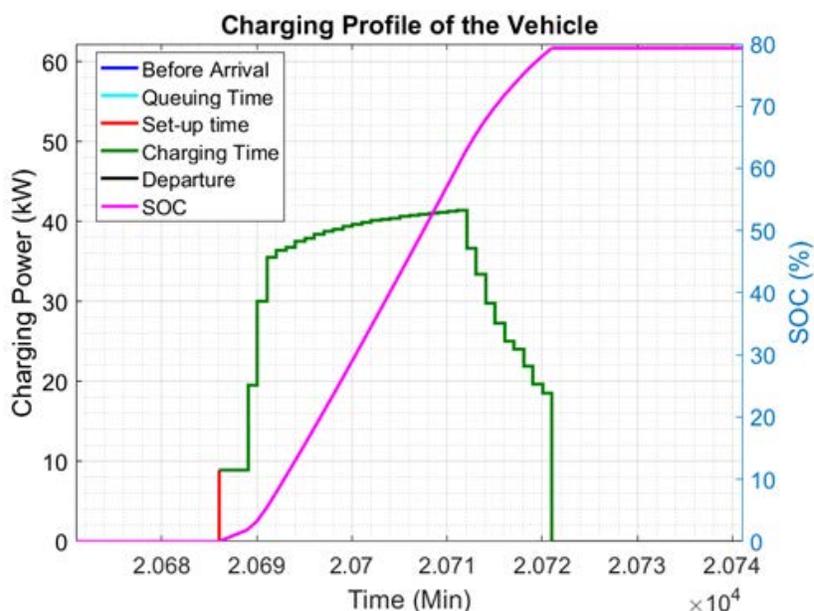


Figure I.3-2 - Example of a charge profile created using the charge acceptance model. The charged vehicle is an EV with a 60 kWh battery capable of fast charging at 50 kW.

The charge acceptance model is based upon vehicle testing performed by INL as a part of the Advance Vehicle Testing Activity.

After the charging demand is calculated, the station controller uses it, along with the station parameters, to allocate power to each charging port. The station parameters and operation, as determined by the station controller, are fed into the cost model to determine the costs of operating the station.

At this point in the project, initial development of the DCFC station model has been complete and the model is functional. Simulations run by the model can determine grid power needs of the station and statistics to characterize the service quality provided to users of the station, like charge duration and wait times.

An initial cost model has been developed for the capital and operating costs of fast charging stations. Given the station parameters and a power profile determined by the station model, the cost model can provide cost estimates for the simulated scenario. Current plans are to integrate cost model functionality into the overall system model in order to streamline the simulation process.

Conclusions

This task has worked towards the development of a model which can simulate the operation and costs of a multi-port fast charging station based on a given set of charging needs. This type of model looks at the charging station as a whole system, which is necessary to capture the level of detail required to evaluate these types of stations. Once the modeling is totally complete and refined, it will be used to understand how different charging strategies will affect station costs and the quality of service provided to its users. This model and its results may be used to assess and inform further SMART Mobility studies. AFI pillar. One option for FY 2018 R&D includes that this task may be merged with AFI task 2.1 to apply the DCFC control model to region-specific scenario planning.

I.4 Engineering Feasibility Assessment of Advanced Fueling Infrastructure - Dynamic Wireless Power Transfer [Task 3.3]

Omer C. Onar, Principal Investigator

Oak Ridge National Laboratory, Power Electronics and Electric Machinery Group
National Transportation Research Center
2360 Cherahala Boulevard
Knoxville, TN 37932
Phone: (865) 946-1351
E-mail: onaroc@ornl.gov

David E. Smith, Principal Investigator

Oak Ridge National Laboratory, Vehicle Systems Research Group
National Transportation Research Center
2360 Cherahala Boulevard
Knoxville, TN 37932
Phone: (865) 946-1324
E-mail: smithde@ornl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$235,000

End Date: September 30, 2017
DOE share: \$235,000

Non-DOE share: \$0

Project Introduction

Transportation accounts to about ~30% of the total energy consumption in the U.S. according to the U.S. Energy Information Administration (EIA). Using domestically generated electrical energy instead of imported oil is a must to secure a sustainable and clean transportation energy system in our country. Electric vehicles (EVs) have attracted considerable attention due to their potential to substantially reduce petroleum consumption and greenhouse gas emissions in the transportation sector. However, there are still barriers against the further commercialization and adoption of EVs. Among these barriers, limited range, range anxiety, and the cost of battery packs are the most important ones. As one means of increasing the adoption rate of EVs, wireless charging has gained considerable momentum due to ease of charging with no wired connection. Wireless charging is a safe, convenient, flexible, and an efficient method for charging the electric vehicles. With dynamic (in-motion) wireless charging, the range of the electric vehicles can be extended, and the size and cost of their battery packs can be reduced. Furthermore, dynamic wireless charging is a key enabling technology for the connected and automated vehicles by automating their charging process, increasing their range, wirelessly connecting them to the power grid, and reducing their battery pack weight with improved fuel economy (reduced energy consumption). The dynamic wireless charging technology is based on the electromagnetic coupling between a roadway electrified with coils or long wire loops under the road surface and a receiver coupler mounted underneath the electric vehicle. Power ratings, track (electrified roadway section) length, electric and electromagnetic field emissions and confinement, efficiency, lateral misalignment tolerance, power transfer continuity, geometric layout and design of the tracks, and resonant tuning configurations are the areas with research needs for the field of dynamic wireless charging systems. This project aims at analyzing vehicle energy consumption levels and accordingly determine the needs of an optimally designed dynamic wireless charging system to be deployed in automated mobility districts for refueling the connected and automated vehicles.

Objectives

The overall project objectives can be summarized as follows:

- Identify vehicle energy consumption levels (including auxiliary energy consumption, i.e., air conditioning, thermal management, etc.) for given vehicle specifications, drive cycles, constant speed operations, and traffic conditions (speed variations).
- Based on the vehicle energy consumption levels, identify the dynamic wireless power transfer (DWPT) requirements and size and design of the DWPT system specifications for a given automated mobility district for connected and automated vehicles.
- Develop an optimization framework for optimal design of the power rating, track length, and placement of DWPT systems by minimizing the power rating, track length, and battery impact while maximizing the range extension or energy delivery to the vehicles for providing charge sustaining operation.
- Analyze the grid requirements and system impact on the grid.

Approach

In a DWPT system, the system components include the electromagnetic couplers, electrical infrastructure (grid), grid-side power electronics including the front-end rectifier and the high-frequency power inverter, vehicle-side power electronics including the rectifier and filter stage, and the resonant tuning components. The power rating and sizing of all these components depend on the vehicle energy consumption levels since the DWPT systems must be sized and designed in order to accomplish charge sustaining mode of operation or considerable range extension. Therefore, energy consumptions of vehicles are evaluated on known duty cycles and constant speed operations. Three major approaches can be used to evaluate the vehicle energy consumption levels:

1- Use physics approximations using road load equations, vehicle weight, frontal cross-sectional area, tire roll resistance, air drag, and acceleration/braking and speed information from drive cycle data.

Air drag: $P_{drag} = \frac{1}{2}v^3A\rho$, Power consumed during acceleration or braking (-): $P_{acc} = \frac{1}{2}v^3\frac{m_c}{d}$, Power consumed by rolling over (tire & road combined) resistance: $P_{roll} = rvm_c g$, Total vehicle power consumption: $P_{total} = \frac{1}{\eta}(P_{drag} + P_{roll} + P_{acc}) + P_{auxiliary}$

The drawback of this method is that the battery to wheel efficiency and the regen efficiency of the vehicle are variable, and they depend on the operating point, temperature, battery state-of-charge, etc. which should be accounted for in this model. In addition, this approximation ignores the auxiliary power consumptions including air conditioner, other vehicle hotel loads, window roll down positions, etc.

2- The other approach is to use the Road Load Coefficients (A, B, C) from ANL's Downloadable Dynamometer Database (D³) in addition to the vehicle specs (curb weight, slug weight, average regen efficiency, average battery to wheels efficiency) where A is the torque (lbf), B is the torque per speed (lbf/mph), and C is the torque per acceleration (lbf/mph²). This method has similar drawbacks to that of the first method. Although some software assumes constant 90% drivetrain efficiency and 40% regen efficiency, these assumptions lead to a large error percentage between the actual and estimated vehicle energy consumption values.

3- The 3rd method is to download power consumption data directly from ANL's Downloadable Dynamometer Database (D³). This data takes into account all the variable efficiencies and variable vehicle auxiliary loads with given test conditions since the test data is obtained from the real vehicle performing the duty cycle on the dyno. Data sets for different air conditioner set points, ambient temperatures, and window roll down positions are available in the database. In this approach, power calculation is obtained directly from the battery, including all auxiliary power consumptions and outputs and returns. Specifications for the vehicle classes

being analyzed are given in Table I.4-1. The point A-to-B constant speed energy consumption modeling for light, medium, and heavy-duty vehicle classes considering the cases with and without auxiliary power are completed. Constant speed modeling energy consumption models can be especially useful where the automated driving infrastructure can potentially eliminate the stop signs and traffic lights. Analysis also include the energy block modeling that includes cases with static stops and dynamic charging. Although the goal of dynamic wireless charging is to enable driving in charge sustaining mode, the range of the vehicle is expanded with the on-board energy storage wherever dynamic wireless charging is not available and it also allows for reasonable units and test cases to visualize order of magnitude of sample scenarios. “Energy block” is illustrated in Figure I.4-1.

Table I.4-1 - Specifications of the vehicle classes analyzed for energy consumption models.

	Light-duty	Medium-duty	Heavy-duty
Description	Passenger vehicle	Delivery truck, shuttle	Tractor-trailer, bus
Weight	4,050 lbs, class 1	18,000 lbs, class 3-5	72,800 lbs, class 7-8
Parameters	Road Load Coefficients: A=29.92 lbf B=0.076 lbf/mph C=0.022 lbf/mph ² W _{battery} =648 lbs	Physical Values: C _d = 0.8 C _{roll} =0.0065 A _f = 5m ² W _{battery} =945 lbs	Physical Values: C _d = 0.75 C _{roll} =0.0065 A _f = 10.2m ² W _{battery} =2285 lbs

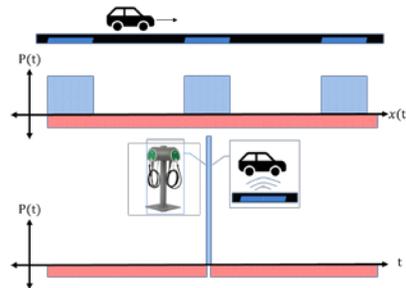


Figure I.4-1 - “Energy Block” modeling illustration for dynamic and static charging cases for an automated mobility district.

Based on the average power consumption of the vehicle and the route length (distance travelled), the dynamic wireless power transfer tracks can be sized. Therefore, the coverage percentage and power requirement of the dynamic wireless power transfer track can be identified. Here, the idea is to determine what scale of dynamic wireless charging system is needed to offset drivetrain energy use to achieve charge sustaining mode. This can be expressed by $kW \times C_{road\%}$ or $kW-mile / 100$ miles terms. For instance, based on 13 kW drivetrain power consumption of a typical EV at 55 MPH speeds, for a 100 mile road, the coverage needed would be 1300 kW – miles. For a 26 kW DWPT system, coverage needed would be 50 miles. For a 130 kW DWPT, coverage needed would be 10 miles (10% $C_{road\%}$). Based on this, the vehicle would receive $130\text{ kW} \times 10\text{ miles} / 55\text{ MPG} = 23.63\text{ kWh}/100\text{ miles}$. On the other hand, for stationary charging, total energy per unit distance approach allows analyzing the overall energy use of vehicles and the time cost of static charging (kWh/mile). Having the same assumption of 13kW drivetrain power at 55 MPH speed, to replenish the 23.63 kWh of energy consumption, for instance, 28 minutes of time is needed for a 50 kW DC fast charger and 12 minutes of time is needed for a 120 kW DC fast charger.

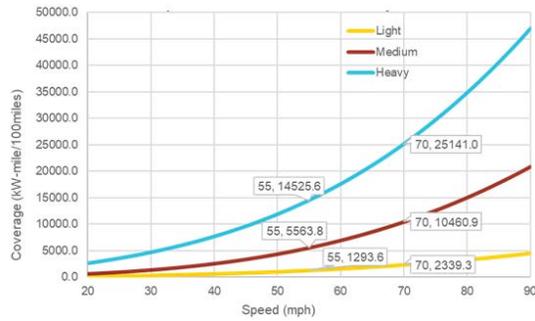


Figure I.4-2 - DWPT coverage assessment for 100 miles of sustained constant speed traveling (drivetrain power only).

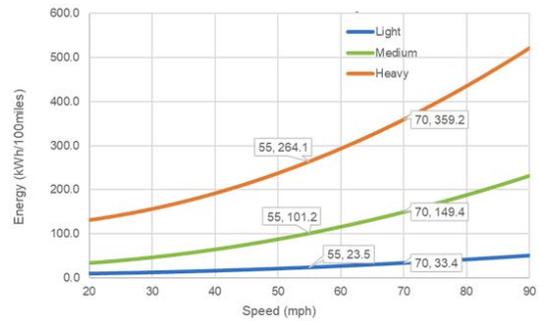


Figure I.4-3 - Energy use (kWh/mile) for 100 miles for sustained constant speed (drivetrain power only).

According to the energy consumption models, the DWPT kW-mile/100 miles coverage assessment for 100 miles for sustained constant speed are given in Figure I.4-2. According to this figure, it is seen that the energy requirements are very large at high speeds. This can be seen as the worst case scenario for what power levels that the couplers should operate. Energy use values (kWh/mile) for 100 miles of sustained constant speed are also given in Figure I.4-3.

Energy consumption of a test vehicle (Chevy Spark EV 2015) is also examined for UDDS drive cycle using the data from D³ test ID #61508013 which uses 23°C test cell temperature, 42% relative humidity, 29 in/Hg barometric pressure, with the cooling fan and air conditioner off, with the vehicle windows down. The average power energy consumption / fuel economy of Chevy Spark on this drive cycle is found to be:

$$\bar{E} = \int_{t=0}^{t=1369} \frac{dP(t)}{dt} \frac{1}{distance} = \frac{1297 Wh}{7.45 miles} = 0.174 kWh/mile$$

Based on the approximate distance of 12,000 meters of the drive cycle, in order to drive the vehicle in charge sustaining mode, i.e., $E_{in} = E_{out}$, the coverage area vs. track power are given in Table I.4-2 (assuming 90% from track to vehicle power transfer efficiency and power transfer continuity along the track). Based on this Table I.4-2, if the entire route is covered by a 4kW dynamic wireless charging track, then the vehicle could be driven in charge sustaining mode. Of course, it is not realistic to cover the 100% of the road or ideally more than 10% of the road. Therefore, initial analysis is performed for a track with ~38kW rated power for the test cases given in Table I.4-3.

Table I.4-2 - Track power, % of the road coverage needed, and track length based on Chevy Spark energy consumption on UDDS drive cycle.

Power to the vehicle	Track power	% of Road coverage	Track length
3.41 kW	~4 kW	100%	12,000 m (entire drive cycle)
6.82 kW	~7.5 kW	50%	6,000 m
13.64 kW	~15 kW	25%	3,000 m
34.10 kW	~38 kW	10%	1,200 m

Table I.4-3 - Summary of test case specifications.

Track power	Track length (each)	# of track sections	Case #
38 kW	1200 m	1	1
38kW	600 m	2	2
38 kW	300 m	4	3
38 kW	150 m	8	4

Based the analysis of these test cases detailed in Results section, it was seen that the location where the DWPT tracks were placed was making large differences in the end-of-the-cycle state-of-charge levels of the vehicle. However, determining optimal power ratings and track placement locations for one drive cycle is not very realistic and repeatable in real life conditions as the traffic flow and vehicle speeds may vary based on the time of the day, season, weather, and other factors. Therefore, a more parametric optimization frame work is needed for determining the system specifications. The optimization can minimize the track length and power rating while aiming to increase the vehicle range.

The range of a vehicle can be increased until charge sustaining or charge increasing mode of operation is reached by increasing the DWPT system coverage and power level. At the same time, longer coverages of the DWPT system and higher powered inverters will cost more. While limiting the track coverage can reduce the construction and installation cost, it will also increase the required power level which increased the track winding cost as well as the cost per grid side unit (including the front-end grid connected rectifier and the inverter). Therefore, optimization should use weighting factors (λ and α) and weights should be varied to analyze the impact of reducing the track length or the power rating of the system. The general form of the multi-objective optimization problem is as follows:

$$\text{Max}_{\substack{0 \leq \alpha \leq 1 \\ 0 \leq \lambda \leq 1}} \{g = \lambda_1 D(x, p) - \lambda_2 M(x, p, \alpha_1, \alpha_2)\} \text{ such that:}$$

$$\lambda_1 + \lambda_2 = 1, \alpha_1 + \alpha_2 = 1, g(x, p) \leq 0, h(x, p) = 0, x_{i, LB} \leq x_i \leq x_{i, UB} \quad (i = 1, \dots, n)$$

where $M(x, p)$ is the system cost while $D(x, p)$ is the vehicle range. The range objective function is formulated as follows:

$$D(x, p) = \frac{\frac{\text{Energy Available}}{E \cdot SOC_i} \cdot \frac{\text{Average Speed}}{\bar{v}}}{\underbrace{\frac{\bar{P}}{\text{Average Tractive Power}} + \frac{P_{aux}(T)}{\text{Auxilliary Power}} - C_{rate} \epsilon_{road\%} \cdot \frac{L_{vehicle}}{L_{sys}} \cdot E \cdot \eta_{coupler}}_{\text{Roadway Power}}} = \frac{kWh \cdot \frac{\text{miles}}{\text{hour}}}{kW + kW - kW} = \text{miles}$$

where $C_d A$ is the drag form factor, M is the total vehicle mass, SOC_i is the initial state-of-charge of battery, v is the speed of vehicle (\bar{v} - average speed), E is the energy storage capacity of the vehicle battery, P_{aux} is the auxiliary power consumption (air conditioner, etc.), g is Earth's gravity, ρ is air density, η_{eq} is overall tractive power efficiency, η_{br} is the overall regenerative braking efficiency, and $\eta_{coupler}$ is the efficiency from coupler underutilization. In addition to the range objective function, the cost objective function can be defined as follows:

$$M(\mathbf{x}, \mathbf{p}, \alpha_1, \alpha_2) = \alpha \left(\frac{\dot{E}_{rate} \epsilon_{road\%}}{L_{sys}} \right) + (1 - \alpha) \frac{\epsilon_{road\%}}{\text{Construction Distance}}, \text{ where the parameter weights are } \alpha_1 + \alpha_2 = 1$$

$\frac{\text{Number of Inverters}}{\text{Mile}}$
 $\frac{\text{Construction Distance}}$

In order to generate the results linking the relationship between the range, average charge rate on DWPT tracks, and the vehicle speed, a Multi-Objective Non-Linear Program (MONLP) is defined and the vehicle range extension through dynamic wireless charging is analyzed with respect to these input parameters.

$$D = \frac{\dot{E} * SOC_i * v_{const}}{\left(\frac{\mu r g}{\eta_{eq}} \right) v_{const} + \left(\frac{C_d A}{M} \right) \frac{v^3}{2 \eta_{eq}} - C_{rate} \epsilon_{road\%} * \dot{E}}$$

Results

This section first summarizes the findings of the test cases shown in Table I.4-3. For DWPT test case #3, four of the 38 kW, 300 m long DWPT tracks are installed between 2000-2300, 3000-3300, 8000-8300, and 11,000-11,300 meters on the route. Negative power indicates vehicle receiving power from the track. At the end of the drive cycle, net energy consumption is positive (313 Wh, 1.64% net decrease in stage-of-charge (SOC)). DWPT Case #3 power and energy variations are shown in Figure I.4-4. In this test case, DWPT tracks are installed in sections where the vehicle speed is faster and the vehicle power consumption is higher. This was tested in an effort to support the vehicle power consumption at high power demand regions on the route. However, since the vehicle speed is relatively higher, vehicle spends less time on the track which in turns reduces the overall energy captured by the vehicle from the DWPT track. For DWPT test case #4, eight of the 38 kW, 150 m long DWPT tracks are installed between 1000-1150, 2000-2150, 4000-4150, 6000-6150, 6450-6600, 8000-8150, 9000-9150, and 11500-11650 meters on the route. These sections are specifically selected as they correspond to the mostly slower traffic flow areas; therefore, vehicle spends more time on the tracks which in turns increases the energy captured from the DWPT tracks. At the end of the drive cycle, net energy consumption is negative (-585 Wh, 3.01% net increase in SOC). DWPT Case #4 power and energy variations are shown in Figure I.4-5. This figure clearly shows that if the DWPT couplers are strategically positioned in low speed / high traffic areas, they can transfer the most energy to the vehicle and they can potentially have the highest benefit for the installation cost.

Using the MONLP detailed in the previous section, the range as a function of vehicle speed and the coverage rate is given in Figure 6 for the initial SOC levels of 100, 75, and 50%. The range graph shown in Figure 6 maps the possible vehicle range values that can be achieved based on the vehicle speed and the maximum charge rate allowed from the DWPT tracks from electrified roadway sections.

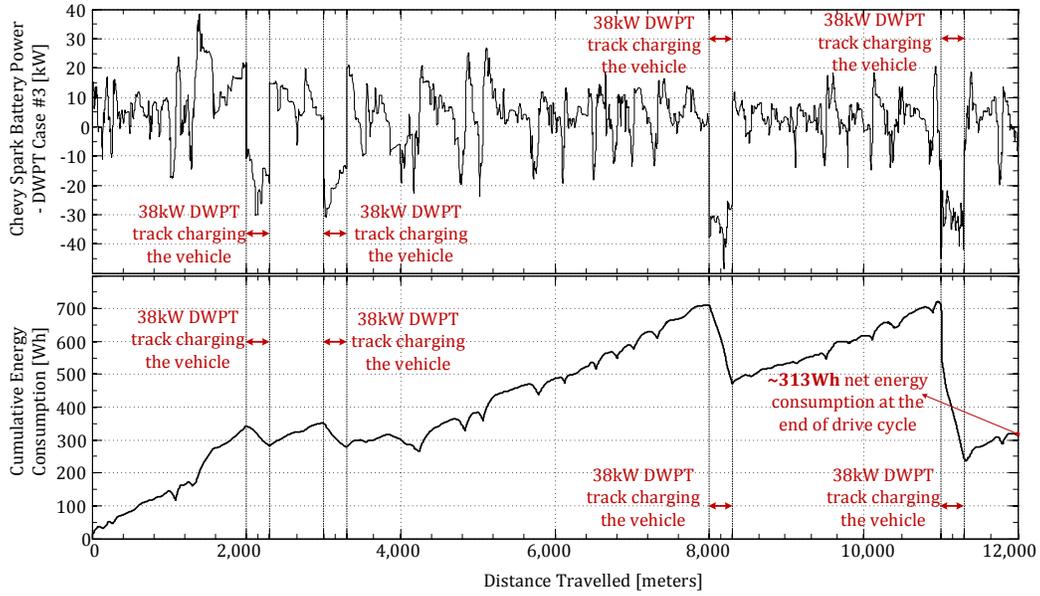


Figure I.4-4 - Distance travelled vs. power and cumulative energy consumption for DWPT test case #3.

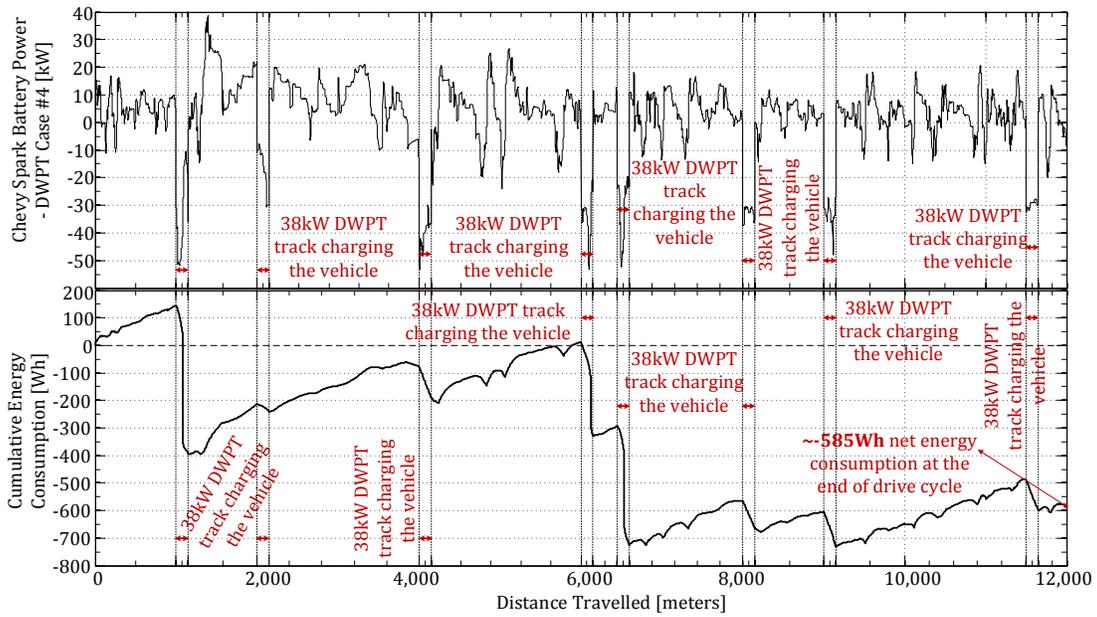


Figure I.4-5 - Distance travelled vs. power and cumulative energy consumption for DWPT test case #4.

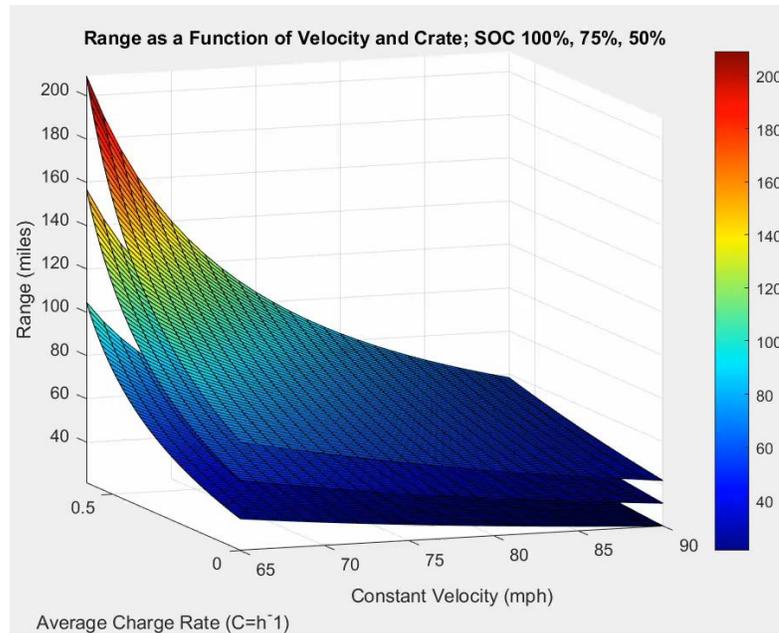


Figure I.4-6 - Range extension through dynamic wireless power transfer with speed and C rate variations by MONLP.

Conclusions

This project analyzed the vehicle energy consumption levels in order to size and design the DWPT tracks. The energy consumption model developed can work at constant vehicle speeds as well as speed variations as a function of time like in a drive cycle. The initial analysis performed on a UDDS drive cycle with a test vehicle data showed that determining the power rating, track length, and placement of track can have significant impact on energy delivery. An optimization framework was developed to analyze the relationship between the range extension through DWPT, power rating of the DWPT tracks, and the vehicle speeds. One proposed option for possible further R&D includes expanding the analysis to generalize the optimization framework while also analyzing the grid requirements and the impact for DWPT systems.

Key Publications

1. A paper is under preparation to be submitted to the IEEE Transportation Electrification Conference and Expo 2018.

I.5 Engineering Feasibility Assessment of Advanced Fueling Infrastructure Integration with the Built Environment [Task 3.4]

Timothy Lipman, PhD, Principle Investigator

Lawrence Berkeley National Laboratory
2150 Allston Way, Ste. 280
Berkeley, CA 94704
Phone: (510) 642-4501
E-mail: E-mail: tlipman@lbl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2018

Total Project Cost: \$134,000

DOE share: \$134,000

Non-DOE share: \$0

Project Introduction

This SMART Mobility Alternative Fuel Infrastructure (AFI) pillar work is motivated by advances in vehicle technology particularly for electric vehicles (EVs) and future autonomous taxi/ride-sharing vehicle fleets. These rapidly evolving concepts are changing the way industry groups and other key stakeholders are thinking about the shape and character of the next several decades of vehicle-based transport. Furthermore, the implications of future fleets of “connected autonomous vehicles” (CAVs) extend beyond motor vehicle transport to integration with public transit systems and impacts on needs for vehicle parking and fueling. With a fleet of increasingly electric vehicles expected in the future based on market and policy drivers (be they fully battery electric, hybrid gasoline-electric, or hybrid fuel-cell electric) the development of the advanced electric and hydrogen fueling infrastructure needed to support these fleets of vehicles becomes a key consideration to their future development.

Objectives

This study examines the potential for four innovative concepts to provide synergies with the built environment with regard to fueling/charging concepts for future fleets of ridesharing/taxi vehicles:

1. Vehicle-grid integration (VGI) concepts, potentially through a building/local interface;
2. High power EV charging with battery storage for reduced impacts;
3. Small scale hydrogen fueling for extended FCV operating area; and
4. Hydrogen, electricity, and waste heat “tri-generation” systems.

The study reviews currently available literature on these topics and finds that there are interesting opportunities for these concepts to reduce the potential costs of advanced fleet vehicle fueling under certain conditions. With regard to VGI concepts, these clearly offer the potential for EVs to help improve the operation of utility grids in ways that can provide economic value at both local distribution and larger grid scales. This could reduce the overall operating costs of future fleets of EVs as those grid values flow back to vehicle fleet owners. The combination of battery storage with high-power EV charging is also complicated and can offer benefits of reduced local power costs, but in ways that are variable between utility areas (based largely on the type of level of demand charges) and that depend on the exact charging and battery system recovery time usage patterns.

The project also develops a set of “levelized cost” spreadsheet models for each of the above use cases that quantifies the electricity and hydrogen costs that could result from the use of these more innovative types of fueling arrangements, allowing for potential changes in key values over time across regions of the U.S. This model will then be available for use within the AFI Pillar and among the other SMART Mobility pillars to compare relative costs of future vehicle fleet fueling with these and other more conventional solutions.

Approach

This project task will be accomplished through a combination of detailed literature reviews, synthesis of the literature, development of a high-level vehicle total-cost of ownership (TCO) spreadsheet model, model specification, and initial economic analysis of the key concepts identified above. The project task is being conducted in coordination with other AFI pillar tasks to share information and avoid duplication of effort.

In the first project phase, a wide range of literature sources on the project focus topics are being examined, assessed, and summarized. In the final (FY 2018) phase, experts in academia, national laboratories, and industry will be consulted for additional project input and the findings of the California Vehicle-Grid Integration (VGI) Working Group will be integrated for understanding the potential grid integration benefits of future fleets or relatively “compliant” EV fleets. Then, once completed, the spreadsheet cost assessment tool will be made available to other AFI pillar and SMART Mobility pillars for inputs to the overall integrated analysis.

Results

Primary accomplishments in this period include:

- Completion of initial thorough literature review of several key concepts that leverage existing and expected investments in energy system infrastructure that can positively impact the economics of future vehicle fueling / charging for advanced vehicle fleets including CAVs used for ride-hailing/sharing applications.
- Initial development of advanced fueling system concepts economic cash-flow spreadsheet model for high-level economic analysis of fleet fuel cost for these integrated fueling concepts, for use among the SMART Mobility pillars.
- A key project milestone was met with a September 2017 interim deliverable report: “Integration of Charging and Fueling Infrastructure with the Built Environment for Future Fleets of Advanced Vehicles” (draft report to be expanded and finalized at end of task).

Conclusions

Initial project work was completed during this period with the project milestone deliverable interim report mentioned above. Based on the work conducted in this period, key findings from the investigation include:

- Emerging electricity and hydrogen fueling options offer potentially attractive economics for future fleets of shared-use (autonomous or human driven) vehicles in certain settings and use patterns; and
- The more controlled and scheduled environments offered by ridesharing fleet vehicles (vs. private owned vehicles that are less subject to scheduling) offer enhanced opportunities for taking advantage of integrated vehicle-grid-fueling concepts.

More specifically, with regard to VGI concepts, these clearly offer the potential for EVs to help improve the operation of utility grids in ways that can provide economic value at both local distribution and larger grid scales. This could reduce the overall operating costs of future fleets of EVs as those grid values flow back to vehicle fleet owners. The combination of battery storage with high-power EV charging is also complicated and can offer benefits of reduced local power costs, but in ways that are variable between utility areas (based

largely on the type of level of demand charges) and that depend on the exact charging and battery system recovery time usage patterns.

Furthermore, the economics of small-scale hydrogen production and distribution remains challenging, with system capital costs being a key driver. However, larger types of tri-generation systems can produce hydrogen at relatively attractive costs and potentially be co-located with fueling depot locations, reducing hydrogen transport costs.

Next project steps will involve further integration of recent findings from the literature and conference presentations on these topics, further development and economic assessment of these concepts using a high-level levelized fuel cost (or project 'pro-forma' type) tool, and final documentation of project methods, findings, and conclusions.

Key Publications

1. Lipman, T.E., J. Szinai, E. Apostolaki-Iosifidou, M. Ghamkhari (2017) "Integration of Charging and Fueling Infrastructure with the Built Environment for Future Fleets of Advanced Vehicles," Lawrence Berkeley National Laboratory Interim Report, U.S. Department of Energy SMART Mobility Program, September.

I.6 Fueling System Design Considerations for Shared-Use EV Taxis [Task4]

Timothy Lipman, PhD, Principle Investigator

Lawrence Berkeley National Laboratory
2150 Allston Way, Ste. 280
Berkeley, CA 94704
Phone: (510) 642-4501
E-mail: tlipman@lbl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2018

Total Project Cost: \$100,000

DOE share: \$100,000

Non-DOE share: \$0

Project Introduction

This SMART Mobility Alternative Fuel Infrastructure (AFI) pillar work, we examine future infrastructure need for potential future fleets of advanced rideshare/taxi vehicles based on vehicle electrification and compared with use of conventional gasoline vehicles. Given a transportation network and historical data of trip demands, a transportation network company (TNC) could then seek to find the optimal sizing (number of chargers) and placement (location) of EV charging stations, as well as the electric vehicle (EV) fleet size by minimizing the total cost. In this project task, we assume the EV fleet size and the corresponding driving demands are given, and we focus on the planning of fueling systems for the EVs, i.e., optimizing the sites and sizes of the EV charging stations to satisfy the demands.

Objectives

This project task effort will:

- Determine the optimal sizing of EV charging stations and vehicle designs (re: battery size), given the trip demands of a specific region for a future shared-use EV taxi fleet;
- Complete literature review, and formulate an optimization problem for coupled transportation and energy networks (FY 2017);
- Develop efficient computational tools for solving the resulting problem for large-scale networks (FY 2018); and
- Lead into integration for further development of Behavior, Energy, Autonomy, and Mobility (BEAM) model at LBNL for larger-scale network modeling with INL and NREL collaboration (FY 2018-19).

The ultimate goal of the task is to develop an efficient and scalable computational platform for use within the AFI pillars and to inform the work of other pillars, involving the complex trade-off of advanced fleet vehicle charging/fueling system design with vehicle battery size/driving range, including economic considerations.

Approach

Considering that the traffic flow and traditional base loads are uncertain over the target-planning horizon, a set of finite potential future scenarios are forecast. Then a two-stage stochastic programming model is adopted to plan fast-charging stations. The objective function for this is formulated as documented in the project interim report, where key elements include the fixed cost of building charging stations and the variable building cost in proportion with the number of charging spots.

Additional considerations account for power distribution network upgrade costs, which include the costs for distribution lines and the costs for substation capacity expansion. Also included are physical power system constraints, the annual expected energy purchase costs of the whole system, and cost penalties for unsatisfied charging demands.

As the cost trade-offs associated with future vehicle fleets based on electrification are developed, they will be compared with conventional vehicle fuel scenarios in terms of operational efficiency and total cost of fleet ownership and operation. The project task is being conducted in coordination with other AFI pillar tasks to share information and avoid duplication of effort.

Results

Primary accomplishments in this period include:

- Initial and revised specification of formalized, least-cost optimization model constraints for assessment of key vehicle battery size and charging system power capacity trade-offs for future fleets; and
- A key project milestone was met with a September 2017 interim deliverable report: “Optimal Planning of Fueling Systems for Shared-Use Electric Vehicles” (draft report to be expanded and finalized at end of task).

Shown below are the results of an initial problem solution based on the detailed problem specification, illustrating the number of Level 2 and high-power fast EV chargers are optimally installed at an example 25-node network. These estimates are now being further validated and extended to larger networks, with results to be integrated into the LBNL BEAM model for larger-scale analysis.

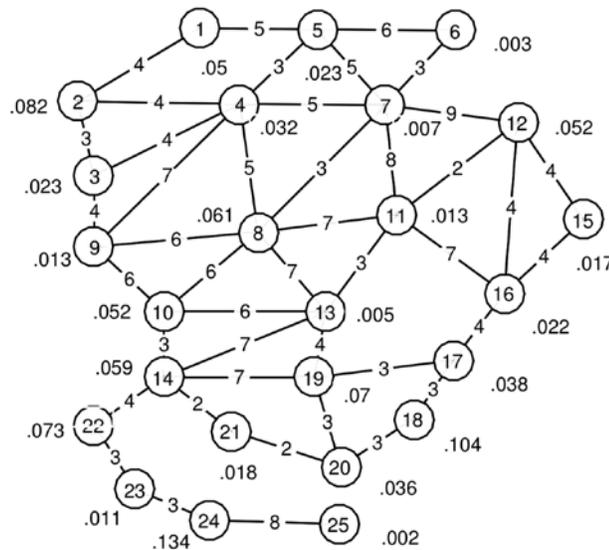


Figure I.6-1 - Example 25-node Transportation Network with Numbers of EV Charger Locations

Conclusions

This task involves formulating a second-order cone-programming model for planning EV charging stations on a transportation network. Based on the proposed model, we conduct numerical experiments to analyze various factor influences on the planning of EV charge networks for future fleets, including EV battery capacities, rated charging power, and charging system scale (e.g., number and types/power level of chargers) at individual nodes.

Key findings from this initial stage of the investigation include:

- Longer driving range for the EV fleet leads to less charging demands and lower investment costs for fueling systems. However, EVs with longer driving range are usually more expensive, and less efficient. The further details of the trade-offs between investments in EV batteries and fueling systems are the subject of the project remaining work.
- Higher charging power results in a lower required number of chargers. However, the investment costs may not decrease significantly with the increase of charging power. That is because higher power chargers and the corresponding grid upgrades are also more expensive. In practice, adopting higher power chargers will reduce the downtime of EVs due to charging and enhance EV utilization. As a result, the total EV fleet size may also be reduced, but with a complex set of trade-offs that are the subject of additional FY 2018 analysis.

Next project steps will involve further testing and validation of the optimization framework, extensions to larger networks, further comparison of study findings to previous efforts, and final documentation of project methods, findings, and conclusions.

Key Publications

1. Zhang, H., C. Sheppard, A. Gopal, T. Lipman, and S. Moura (2017) “Optimal Planning of Fueling System for Shared-Use Electric Vehicles,” Lawrence Berkeley National Laboratory Interim Report, U.S. Department of Energy SMART Mobility Program, September.

II. Smart Mobility–Connected and Automated Vehicles (CAVS)

II.1 Connected and Automated Vehicles National-level Adoption and Energy Impacts of CAVs [Tasks 2B1 and 2B2]

Thomas Stephens, Principal Investigator

Argonne National Laboratory
9700 S. Cass Avenue
Lemont, IL 60439
Phone: (630) 252-2997
E-mail: tstephens@anl.gov

Jeffrey Gonder, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-4462
E-mail: Jeff.Gonder@nrel.gov

Zhenhong Lin, Principal Investigator

Oak Ridge National Laboratory
2360 Cherahala Blvd.
Knoxville, TN 37932
Phone: (865) 946-1308
E-mail: linz@ornl.gov

David Anderson and Rachael Nealer, Program Managers

U.S. Department of Energy
Phone: (202) 287-5688, (240) 364-4093
E-mail: David.Anderson@ee.doe.gov, Rachael.Nealer@ee.doe.gov

Start Date: October 1, 2016

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Total Project Cost: \$1,722,000

DOE share: \$1,722,000

Non-DOE share: \$0

Project Introduction

The potential impacts of connected and automated vehicles (CAVs) on transportation energy use are large and highly uncertain. Much of this is due to uncertainty in future adoption levels and patterns of use as well as the effects of CAVs technology on vehicle efficiency. Previous studies give wide ranges of estimated changes in travel and energy intensity due to CAVs.

Models and simulations of CAVs use are necessarily limited to specific cases and geographic regions (corridors, metropolitan areas). Such simulations need well-founded estimates of future CAVs adoption. Results from these simulations need to be expanded to the national level.

Objectives

This project reviewed and synthesized existing literature and current knowledge to assess the most important information gaps and is developing methods to take results from detailed modeling and simulation of CAVs deployment and expand them to the national level. This project will provide national-level estimates of CAVs adoption and resulting energy use.

Approach

In order to establish bounds on potential energy use by future CAVs and to identify the key knowledge gaps, relevant studies were reviewed and from these the state of knowledge of potential energy and market implications of CAVs for passenger travel energy use were assessed, and information on consumer costs affected by CAVs was reviewed. Based on this review, lower and upper bounds on CAVs energy use by light-duty passenger vehicles in the U.S. were estimated, and key uncertainties/knowledge gaps were identified.

To provide better estimates of energy use, three related tasks are addressing CAVs technology adoption, changes in travel behavior, and changes in on-road vehicle energy use across the U.S.

The ORNL MA3T modeling approach is being extended to give projections of future adoption of shared mobility, and highly automated and connected vehicles. Transferability modeling is being used to develop national-level estimates of changes in travel metrics (VMT, trips per day, distance per day) from simulations performed at the regional level (in Task 7A.1.3 and related tasks). Thirdly, a framework is being developed to estimate on-road energy use by vehicles with these travel patterns by road type/condition across the U.S. The result will be national-level energy impacts accounting for changes in CAVs adoption levels, travel behavior changes and changes in vehicle energy efficiency.

Results

Bounds on energy impacts of CAVs for passenger travel are estimated based on a review of literature (Stephens et al, 2016). Consumer costs impacted by CAVs were also reviewed. Energy use bounds were estimated based on combined effects on travel demand (vehicle-miles-traveled, VMT) and vehicle efficiency. The VMT impact calculations included vehicle occupancy assumptions to translate between person miles traveled (PMT) and VMT. The efficiency calculations relied on literature-reported values for different CAV feature impacts on fuel consumption rates (e.g., due to vehicle-to-infrastructure communication / coordination, vehicle platooning, etc.), and also include a first-order disaggregation of each feature's impact in different driving situations (i.e., city vs. highway driving and travel at peak vs. off-peak times). The relative impacts were then weighted by the amount of driving that takes place in those different situations.

Estimated impacts were synthesized into three CAVs scenarios: Partial (partial automation with some connectivity), Full-No Rideshare (full automation with high connectivity without ridesharing) and Full-With Rideshare: (full automation with high connectivity with ridesharing). Partial automation was assumed to include technologies such as driver assistance that still require an attentive driver to control the vehicle, corresponding to SAE levels 1 or 2 (SAE, 2016), with limited connectivity. Full automation was assumed to correspond to SAE Levels 4 and 5, allowing vehicle operation without an attentive driver (or even without a person in the vehicle), and with connectivity permitting communication between travelers, vehicles, traffic control devices, and traffic control centers. Ridesharing refers to a net increase in vehicle occupancy resulting from two or more people riding together in a vehicle during some or all of their travel.

The upper bound estimates for each scenario assume maximally energy increasing combinations of CAV effects on VMT and vehicle efficiency (i.e., many more miles traveled with little or no fuel economy gains), whereas the lower bound estimates assume the reverse (i.e., minimal increases in VMT combined with more aggressive vehicle efficiency improvements). The results (summarized in Figure II.1-1) illustrate wide separation between the scenarios' upper and lower bounds on U.S. LDV fuel use, reflecting the large uncertainties in CAVs' impacts on both vehicle fuel consumption rates and VMT. The upper bound for the Full-No Rideshare scenario represents the highest increasing fuel use case with triple the annual fuel use of the base scenario. The lower bound of the "Full-With Rideshare" scenario represents the lowest decreasing fuel use case with less than 40% of the base scenario's fuel use. In contrast, the partial automation scenario shows a much more modest range of impacts, on the order of $\pm 10\%$ for the upper and lower bounds relative to the base scenario.

The figure also highlights the most important factors influencing the upper and lower bounds on fuel use. For the upper bound cases, large VMT changes due to easier travel (faster travel and reduced travel time cost) serve as the largest driver on increasing fuel consumption, with empty travel by driverless CAVs and increased fuel consumption per mile due to high-speed travel representing the next most influential factors. In the lower bound scenarios, decreased fuel use is largely due to aggressive vehicle and powertrain downsizing, combined with smoother driving and only modest VMT increases (which can be further offset by ridesharing).

The wide range between the lower and upper bounds on future vehicle energy use reflects the large uncertainties in ways that CAVs can potentially influence vehicle efficiency and use through changes in vehicle design, driving, and travel behavior. In addition, significant future CAV technology adoption rates are very uncertain. Use of alternative powertrain technologies such as electric drive is likely to reduce both the upper and lower bounds on fuel consumption for the examined scenarios. However, the relative impact of different CAV features in advanced powertrains is expected to differ from that in conventional vehicles, so further analysis would be required to explore the combined impacts of advanced powertrain and CAV technologies.

For each of the factors examined in this report, the most significant drivers of possible fuel use changes have been identified. The most important knowledge gaps in each of these factors have also been assessed and prioritized. Research needed to address these gaps includes assessing potential changes in travel demand due to CAVs, estimating future CAV adoption, analyzing potential effects on vehicle efficiency and redesign, and estimating future heavy-duty CAV energy impacts.

To estimate possible adoption levels of CAVs as well as shared mobility services, the MA3T model was expanded to include choices of buying a CAV, use of shared mobility (either conventional vehicle or CAV) or use transit (Lin, 2017). Figure II.1-2 shows the expanded choice structure. These include elements relevant to the VTO Energy Efficient Mobility System research, as indicated in the lower right panel of Figure II.1-2. Preliminary results include the projected sales shares by fuel type for human-driven and automated vehicles, projected sales shares by automation, and the impact of automation on vehicle ownership.

Transferability modeling is being developed to take results from regional simulations of CAVs to estimate changes in travel demand (VMT) at the national level (Stephens et al, 2017). Under a related SMART Mobility task, Argonne is developing simulations of CAVs in the Chicago metropolitan region and will give projected changes in travel patterns under different conditions of interest. In this task, transferable variables such as total daily trip rates and travel times for each individual will be derived from POLARIS simulation results for CAV scenarios. A two-step clustering algorithm is used to assign people into homogeneous groups through which various types of lifestyles are captured, followed by estimating joint models of number of daily trips and total travel time within each cluster. Finally, using an artificial neural network model, cluster membership rules are transferred to the national level data and the estimated joint models are simulated within the corresponding clusters. Comparison of distributions of transferred variables in the regional and national contexts for current conditions indicate that the platform is capable of transferring travel behavior to the national level with a high level of accuracy. For transferring number of daily trips and total daily travel time, ten clusters were identified and distributions of these travel metrics were estimated. For validation, these distributions were compared with distributions for the national-level households assigned to the clusters identified in the regional data. The transferred distribution of trip rate (number of trips per day) is compared with the observed distribution for one of the clusters in Figure II.1-3. This shows good agreement, typical of the other clusters. This validation adds confidence in the transfer modeling, but further validation is planned which will compare results from POLARIS simulations of cooperative adaptive cruise control (CACC) in southeastern Michigan with results transferred from POLARIS simulations of CACC deployed in the Chicago region.

A framework for rolling up energy impacts at the vehicle level, estimated adoption levels, and changes in VMT to give national-level impact estimates has been developed (Kontou et al, 2017). Initially focusing on passenger travel in light-duty vehicles, the framework accounts for technological progress in CAVs and non-

CAVs in the fleet to capture potential spatial and temporal energy impacts of CAVs. It allows national-level scenarios with transparent and consistent assumptions to be applied. Information flows in the framework are shown in Figure II.1-4.

To exercise the framework, initial placeholder assumptions were used for future CAVs adoption levels, on-road fleet mix of powertrain types, VMT changes, vehicle-level fuel economy impacts and other inputs. Some inputs were taken from EIA's Annual Energy Outlook (AEO) or other scenarios. Figure II.1-5 shows projections developed for several scenarios: Base-AEO (based on AEO 2017 Reference case), Base-ADOPT (based on AEO 2017 with projected vehicle sales shares from the NREL ADOPT model), CACC-AEO (with CACC applied to the Base-AEO case), CACC-ADOPT (with CACC applied to the Base-ADOPT case), AutoTaxi-AEO (with automated taxis applied to the Base-AEO case) and AutoTaxi -ADOPT (with automated taxis applied to the Base-ADOPT case).

These example results show the functioning of the framework and are not to be interpreted as predictions. As seen in Figure II.1-5, these CACC scenario assumptions result in increased fuel consumption (overall VMT increases and some shifts to higher consuming high speed bins). Differences between the two baseline projections show the importance of defining baseline assumptions to permit meaningful comparison of scenarios. These initial demonstrations show the capability of the developed framework to estimate national-level LDV fuel consumption based on parameterized inputs, including powertrain and CAV technology market share, vehicle energy efficiency changes, and VMT changes. More refined inputs will allow further exploration of energy impacts for differing CACC and AutoTaxi use cases, as well as additional CAVs technology scenarios.

These results demonstrate the significant progress that has been made in the challenging but critical tasks of developing methods to expand vehicle-level and regional-level CAVs modeling and simulation results of CAVs to make national level energy impact estimates. Further refinement and validation are needed and are planned for FY 2018.

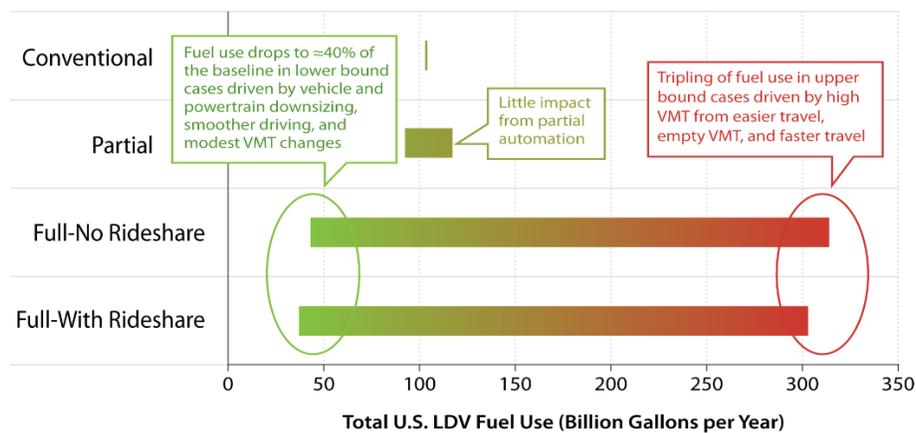


Figure II.1-1 - Estimated bounds on total U.S. LDV fuel use per year under the base (Conventional) and three CAV scenarios, based on the study's synthesis approach from CAV feature impact ranges reported in reviewed literature

Figure from Stephens et al, 2016.

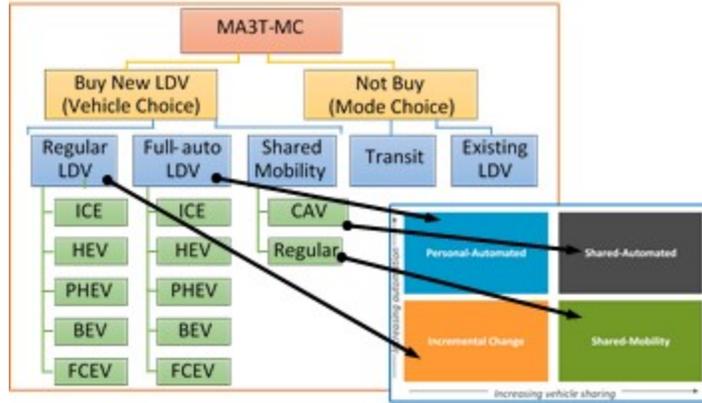


Figure II.1-2 - MA3T-MC choice structure aligns with EEMS future state narratives framework

Figure from Lin, 2017

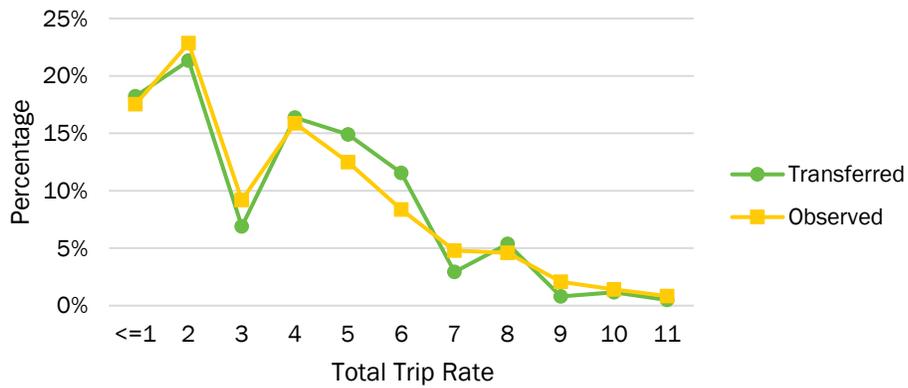


Figure II.1-3 - Comparison of observed and transferred daily travel time
Figure from Shabanpour et al, 2017.

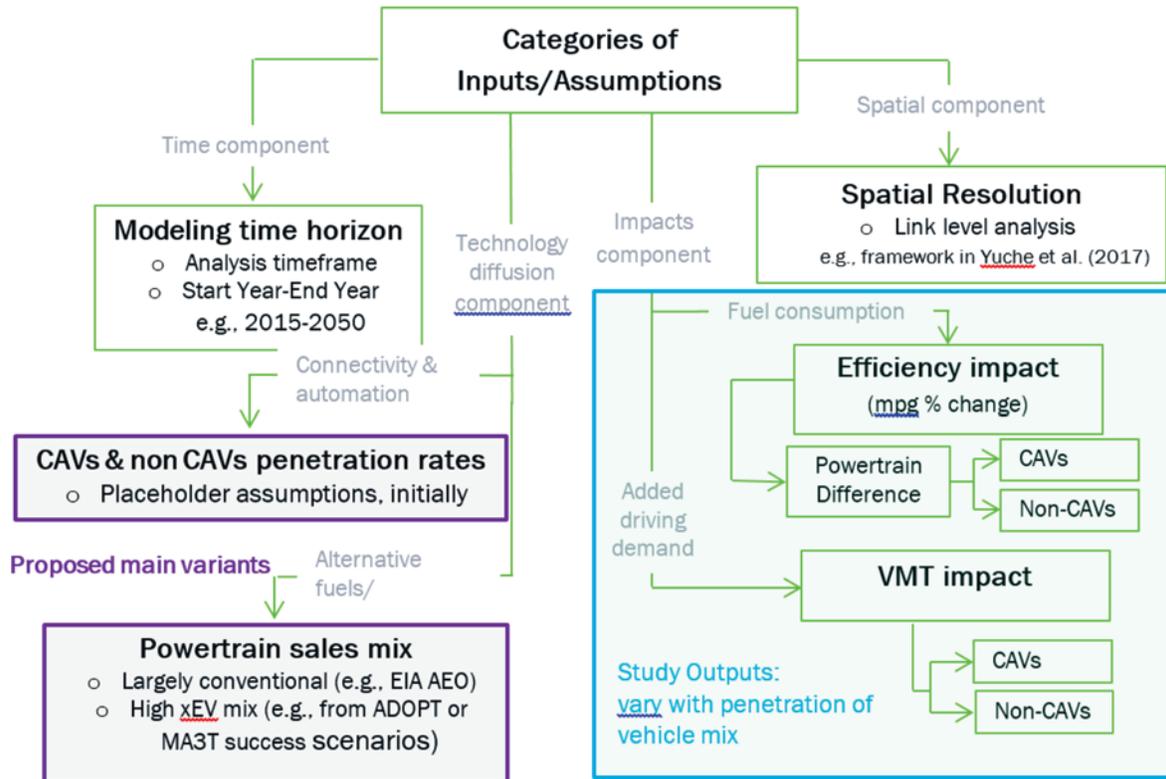


Figure II.1-4 - Modeling Framework for National Analysis

Figure from Kontou et al, 2017.

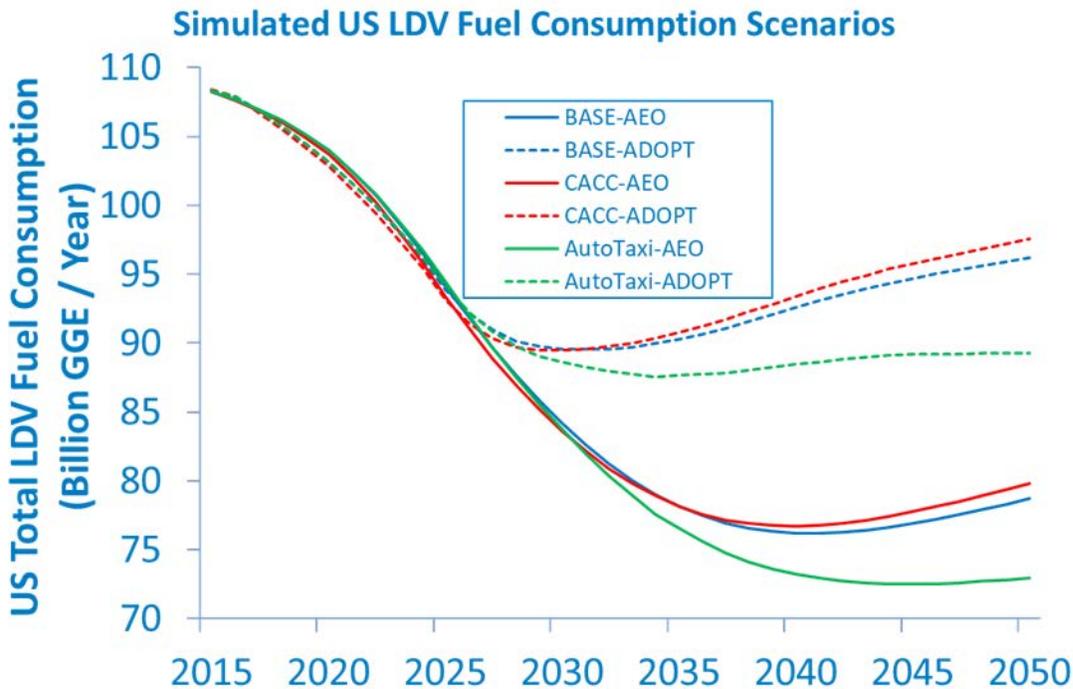


Figure II.1-5 - Example Outputs of the National Analysis Modeling Framework Using Placeholder Input Assumptions

Figure from Kontou et al, 2017

Conclusions

The range of potential impacts of CAVs on energy use by the U.S. transportation sector is large and highly uncertain. Upper and Lower bounds of these energy impacts were estimated from a synthesis of recent studies and available data. Important areas requiring significant research and analysis to reduce uncertainties include assessing potential changes in travel demand due to CAVs, estimating future CAV adoption, analyzing potential effects on vehicle efficiency and redesign, and estimating future heavy-duty CAV energy impacts.

Methods to estimate potential adoption of CAVs technologies are being developed by extending the MA3T model to capture new mobility choices made available through CAVs. Such estimates will be useful in SMART Mobility CAVs tasks that are modeling CAVs use at a regional or local level. Methods to expand vehicle-level and regional simulation and modeling results of CAVs are being developed and show good progress through the initial validation of the methods. Very preliminary demonstration of aggregation methods show the capability of the developed framework to estimate national-level LDV fuel consumption. As vehicle-level and regional-level results become available from related SMART Mobility tasks, these expansion methods will be refined and applied to deliver national-level energy impacts results.

Key Publications

1. Stephens T.S., J. Gonder, Y. Chen, Z. Lin, C., C. Liu, and D. Gohlke (2016) "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles," National Renewable Energy Laboratory Technical Report NREL/TP-5400-67216, <http://www.nrel.gov/docs/fy17osti/67216.pdf>

2. Lin, Z. (2017) "MA3T-MobilityChoice: Analyzing the Competition, Synergy and Adoption of Fuel and Mobility Technologies," 2017 U.S. DOE Vehicle Technologies Office Annual Merit Review poster EEMS024, <https://energy.gov/eere/vehicles/downloads/vehicle-technologies-office-merit-review-2017-ma3t-mobilitychoice-analyzing>.
3. Stephens T.S., J. Auld, J. Gonder, Y. Chen, Z. Lin, K. Mohammadian, and R. Shabanpour (2017) " Vehicle Technologies Office Merit Review 2017: Expanding Regional Simulations of CAVs to the National Level and Assessing Uncertainties," 2017 U.S. DOE Vehicle Technologies Office Annual Merit Review poster EEMS026, <https://energy.gov/eere/vehicles/downloads/vehicle-technologies-office-merit-review-2017-expanding-regional-simulations>.
4. Kontou E., Y. Chen, J. Gonder (2017) "CAVs National-Level Energy Impacts: Methodology & Demonstration," National Renewable Energy Laboratory," presented at the 2017 Automated Vehicles Symposium Energy and Environment breakout session San Francisco, July.
5. Shabanpour R., J. Auld, A. Mohammadian and T.S. Stephens (2017) Developing a Platform to Analyze Behavioral Impacts of Connected Automated Vehicles at the National Level, Paper 17-06283, 96th Annual Meeting of the Transportation Research Board, 8-12 Jan, Washington, DC.

II.2 Definition of Connected and Automated Vehicle (CAV) Concepts for Evaluation [Task 7A.1.1]

Steven E. Shladover, Sc.D., Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road
Berkeley, CA 94720
Phone: (510) 665-3514
E-mail: SEShladover@lbl.gov

Jeffery Greenblatt, Ph.D., Co-Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road
Berkeley, CA 94720
Phone: (415) 814-9088
E-mail: JBGreenblatt@lbl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$50,000

End Date: September 30, 2017
DOE share: \$50,000

Non-DOE share: \$0

Project Introduction

This project was initiated to define a common set of CAV applications for subsequent analysis in the DOE SMART Mobility program, so that analyses by researchers and different labs and even in different Pillars of SMART Mobility can start from a common set of assumptions about the CAV systems to be analyzed. By starting from consistent assumptions about the concepts of operations for the systems being studied, the results from the different studies should be comparable on an “apples to apples” basis, so that some synergies can be gained by combining and comparing the results from the different studies. In the absence of such common assumptions, it would be much more difficult to draw robust conclusions about the likely impacts of the different CAV applications on energy consumption and petroleum usage.

Objectives

The objectives of this project are primarily associated with improving communication and coordination among the research teams working in DOE SMART Mobility so that they can learn from each other and so that their results can be compared and combined in meaningful ways. These include:

- Adopting common terminology to describe CAV systems so that it is clear whether researchers are talking about the same or different things.
- Avoiding use of vague and misleading terminology
- Being precise about describing the functionality of the systems that are being analyzed
- Providing consistent assumptions about the expected levels of deployment of each CAV application for analyses predicting future-year impacts,

- Settling on a manageable size collection of CAV applications for analysis, sufficient to span the diversity of likely applications, yet small enough in number that they can be studied within reasonable resource constraints.
- Avoiding unnecessary overlaps or duplications in the applications that will be studied so that the work can be done efficiently.

The project has defined the set of dimensions to use to characterize the diverse CAV use cases, and then used them to describe a set of example use cases for in-depth study. These use cases include private vehicle, public shared use vehicles and goods movement vehicles, using different mixes of connectivity and automation to facilitate their operations. For each of these use cases, the project also estimated low, medium and high levels of implementation for the target study years of 2030, 2040 and 2050.

Approach

The first step was to define the dimensions to use to characterize the different CAV concepts of operation, which were chosen to be:

- Connected or unconnected (autonomous)
- Distribution of functions between driver and automation system, based on SAE J3016 levels of automation
- Operational design domain (limitations on conditions in which the automation is capable of functioning)
- Vehicle class (size and passenger vs. freight)
- Powertrain technology
- Business model to govern operations.

In the second step, fourteen example concepts of operation were defined to represent the diversity of potential CAV systems. These were clustered into groups based on common types of service provided:

- Eco-driving (2)
- Urban mass transport (3)
- Automated taxi systems (2)
- Goods movement systems (3)
- Passenger car automation systems (4).

Finally, the levels of implementation of each of the fourteen systems were estimated for the target study years of 2030, 2040 and 2050, based on assumptions ranging from low to medium to high. These were characterized in terms of the fraction of the vehicle miles traveled for the functions that would be performed using each of the CAV systems in those target future years.

While the creation of the material was done at LBNL, it was reviewed by participants from the four other Labs participating in SMART Mobility and their inputs were incorporated into the final report.

Results

The use case dimensions that were defined to characterize CAV systems were:

- Connected vehicles without any automation

- Automated Systems, characterized by:
 - Connected or Unconnected (autonomous) implementations
 - Five SAE Levels of Automation (L5 – Full automation was not included):
 - L0 – No driving automation
 - L1 – Driver assistance
 - L2 – Partial automation
 - L3 – Conditional automation
 - L4 – High automation
 - Operational design domain (ODD) (roadway type, traffic conditions and speed, geographical boundaries, weather and lighting conditions, coping with anomalies, reliance on roadway infrastructure....)
- Classes of vehicles
 - Passenger vehicles (4 size classes)
 - Freight vehicles (4 size classes)
- Powertrain technologies
 - Conventional gasoline
 - Conventional diesel
 - Natural gas
 - Hybrid gasoline or diesel
 - Plug-in hybrid
 - Battery electric
 - Hydrogen fuel cell
 - Externally-supplied electricity (catenary or inductive)
- Business models
 - Private use
 - Short-term rental/ car share
 - Transportation network company
 - Public transit-like (fixed or semi-fixed route)
 - Private goods delivery
 - Common carrier goods delivery.

The fourteen example applications or use cases were defined to be:

Eco-driving systems

- (1) I2V cooperative eco-driving support for SAE Level 0 manually driven vehicles
- (2) Urban eco-signal control with I2V communication to SAE Level 1 vehicles.

Urban mass transport systems

- (3) Laterally guided bus (Level 1) on busway
- (4) Highly automated bus (Level 4) on busway
- (5) Semi-fixed-route automated shuttle vehicle (Level 4).

Automated Taxi services

- (6) First-generation low-speed automated urban taxi (Level 4, severely limited ODD)
- (7) Advanced automated taxi (Level 4, broader ODD).

Automated goods movement services

- (8) Basic truck platooning (Level 1)
- (9) Advanced truck platooning (Level 1 leader, with Level 3 or 4 followers for freeway use)
- (10) Low-speed urban goods distribution robot (Level 4 within severely limited ODD).

Automated private personal vehicles

- (11) Cooperative adaptive cruise control (CACC) or platooning (Level 1)
- (12) Urban freeway automated driving (Level 4)
- (13) Intercity freeway automated driving (Level 4)
- (14) Automated highway system (Level 4 with close infrastructure cooperation).

A few examples can illustrate the diversity in the estimates of how widespread the use of these systems will be in future target years, based on the percentage of the vehicle miles of travel in their respective market segments that they are expected to serve. First, for the transit applications, Figure II.2-1 shows how the least sophisticated of the systems, with only Level 1 automation, peaks in estimated usage in 2040, to be superseded by the more sophisticated systems with higher levels of automation by 2050:

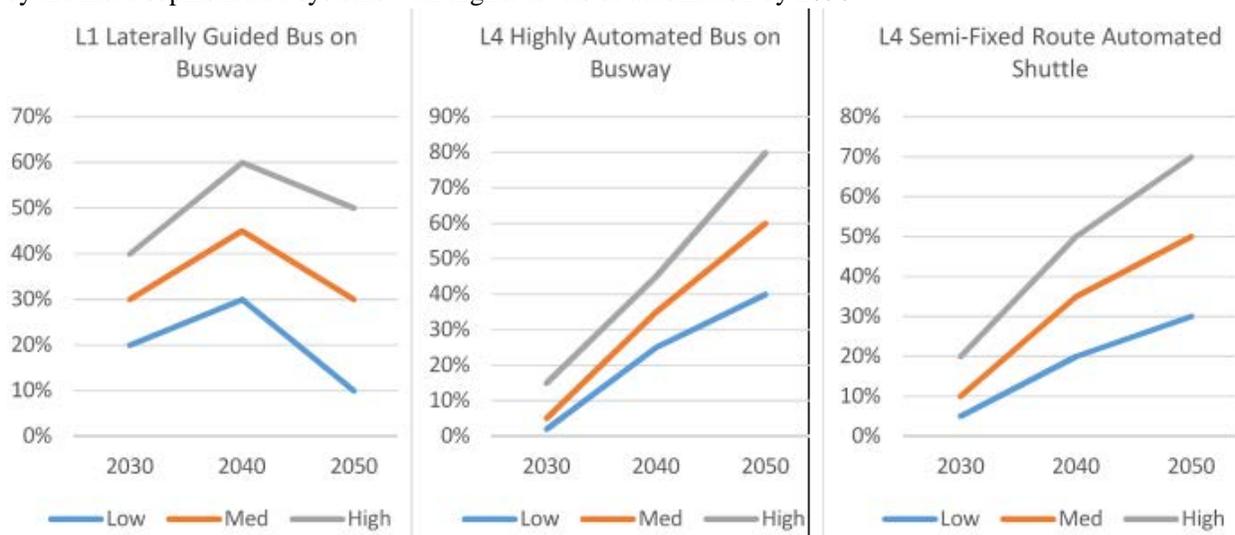


Figure II.2-1 - Predictions of Market Penetrations of CAV Transit Applications

Similarly, for goods movement systems, Figure II.2-2 shows the basic truck platooning concept starting strong during the initial two periods for evaluation, but then declining in the later period as it is superseded by the more advanced goods movement concepts, with highly

automated following vehicles, and the low-speed urban goods distribution robots are shown starting at a low level of deployment because of the immaturity of their technologies, and then growing more significantly in the later years as their technologies mature.

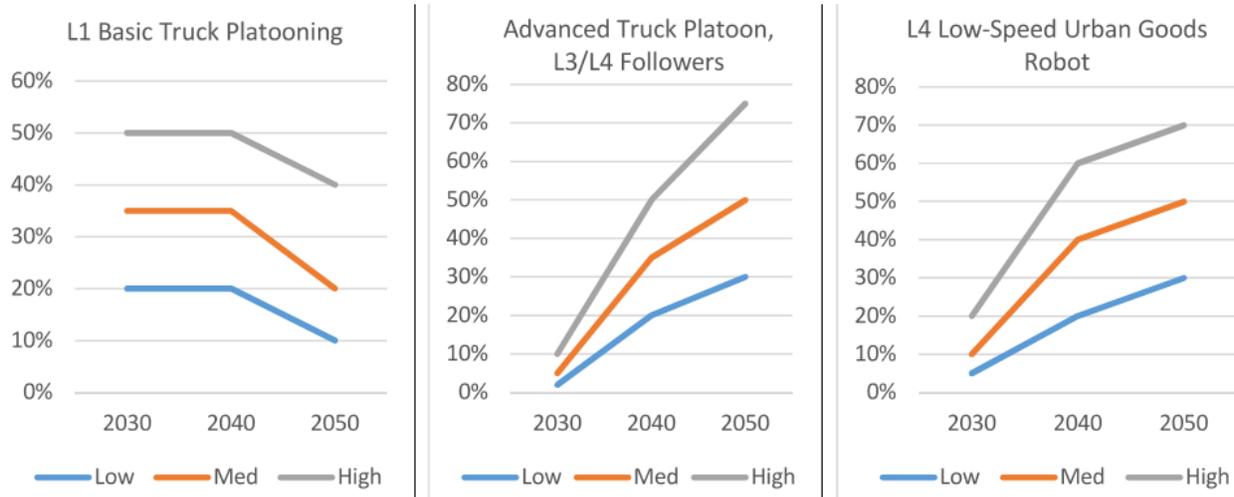


Figure II.2-2 - Predictions of Market Penetrations of CAV Goods Movement Applications

Similar predictions of market share were made for urban taxi services of two different levels of sophistication, for two different levels of eco-driving and for four categories of automation of private passenger vehicles, ranging from cooperative ACC in the near term to automated highway systems with dedicated lanes for the highly automated vehicles. These last two projects are shown in Figure II.2-3, indicating that the CACC is likely to peak in the 2040 period, and then be superseded by the more highly automated systems by 2050. Note that one needs to be careful to not add the high predictions for different systems in the same target years, because the high usage of one of these applications is likely to be combined with the low usage of the complementary application.

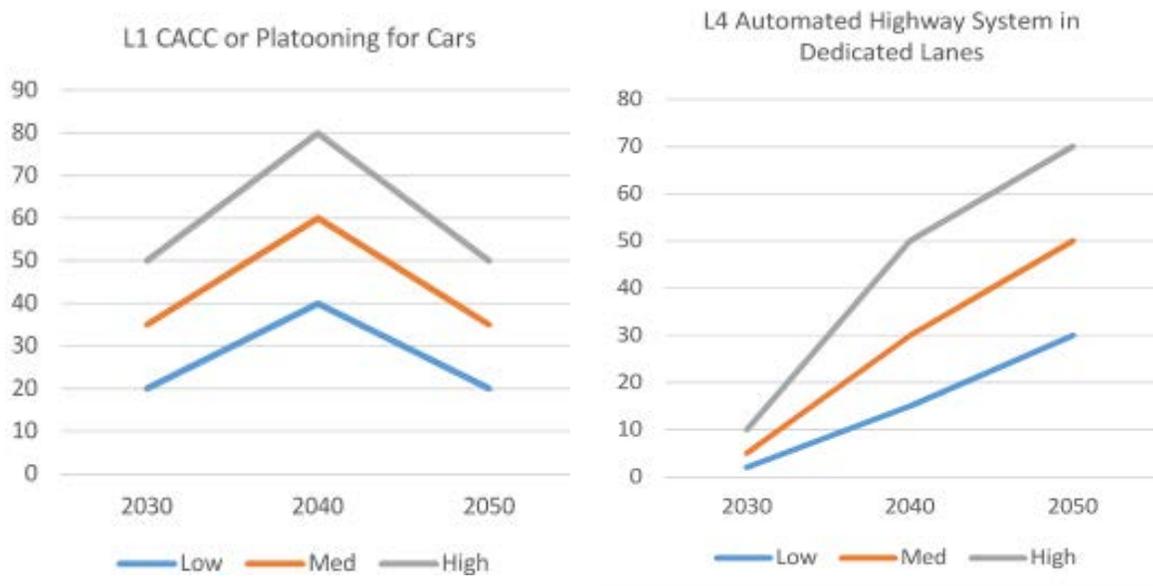


Figure II.2-3 - Predictions of Future Market Penetrations of Low and High Automation Systems for Use on Limited-Access Highways

Conclusions

This study completed its objectives of defining a basic set of use cases for analysis that effectively span the range of likely alternatives for use of CAV technology to improve mobility and save energy. These were vetted

by the full CAV Pillar team and were adjusted to reflect the inputs received from the rest of the participants in the CAV Pillar. These use case descriptions, with the estimates of their low, medium and high levels of utilization in future years, are now available for use by other researchers so that they can produce consistent analyses of the energy impacts of CAV technology.

Key Publications

1. S.E. Shladover and J.B. Greenblatt, Connected and Automated Vehicle Concept Dimensions and Examples, Report of Energy Analysis and Environmental Impacts Division, Lawrence Berkeley National Laboratory, October 2017.

II.3 Traffic Microsimulation of Energy Impacts of CAV Concepts at Different Levels of Market Penetration [Task 7A1.2]

Steven E. Shladover, Sc.D., Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road
Berkeley, CA 94720
Phone: (510) 665-3514
E-mail: SEShladover@lbl.gov

Xiao-Yun Lu, Ph.D. Co-Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road
Berkeley, CA 94720
Phone: (510) 665-3644
E-mail: XiaoYunLu@lbl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016	End Date: September 30, 2019	
Total Project Cost: \$681,000	DOE share: \$681,000	Non-DOE share: \$0

Project Introduction

This project is developing and applying traffic microsimulation tools to predict the impacts that connected and automated vehicle (CAV) systems are likely to have on traffic and energy consumption. The CAV systems only exist today in very limited numbers of prototype vehicles with limited capabilities, which makes it impossible to do realistic field tests that can directly measure traffic or energy consumption impacts. Consequently, it is necessary to depend on large-scale use of simulations to predict what would happen when the CAV systems are deployed in large numbers. Producing realistic estimates of the impacts is challenging because it requires high-fidelity models that are sensitive to the changes in vehicle behaviors that will occur when they are equipped with CAV technology.

Objectives

The project objectives include:

- Refining traffic microsimulation models that were developed under previous research projects supported by the U.S. DOT so that they can represent a wider range of CAV alternatives
- Extending previous traffic microsimulation models from freeway applications to urban signalized arterial applications, including the vehicle interactions with the traffic signal control systems
- Integrating the traffic microsimulations with post-processing to produce estimates of the energy consumption derived from the vehicle motion trajectories
- Applying the traffic microsimulations to diverse transportation networks, including rural and urban freeway environments, high-density and low-density signalized arterial corridors, and environments with both high and low percentages of truck traffic, so that the differences in energy impacts can be better understood to support subsequent national impact projections

- Producing estimates of the energy that can be saved for different levels of market penetration of automation systems operating at different levels of automation, both with and without connectivity, in specific scenarios that can be extrapolated to represent national impacts.

Approach

This project builds upon a set of traffic microsimulation models that were previously developed at the University of California's PATH Program, based on the NGSIM Oversaturated Flow Model implemented on the Aimsun microsimulation platform. These models already include many enhancements to produce more realistic representations of normal drivers' car following and lane changing behavior, plus car-following models for cooperative and uncooperative (autonomous) adaptive cruise control systems for cars and heavy trucks that were calibrated directly from PATH experiments on full-scale cars and trucks. The truck response and fuel consumption data were derived from current research in SMART Mobility Task 7A3.1. The fuel consumption is being estimated using MOVES, and those estimates are being calibrated against the real vehicle test data and potentially other energy consumption modeling tools.

Additional model enhancements that are being implemented in the next stages of work in the project include representations of signalized arterial driving conditions for vehicles using ACC and CACC systems, coordinated merging and lane changing behaviors under both manual and automatic vehicle control, and V2I/V2V coordinated eco-driving strategies for signalized intersections and corridors.

Results

The simulation studies during this first year of work have been concentrated on applications in freeways, based on models of the vehicle-following performance of adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) systems for cars and heavy trucks. Although the ACC and CACC systems represent Level 1 automation, their car following behavior is essentially the same as the car following behavior expected from vehicles that use higher levels of automation, so these results can be generalized for the most part to those higher automation levels. The important distinction is between the autonomous automation systems (those that do not do active coordination) and the cooperative automation systems (which use V2V communication to actively coordinate their behaviors).

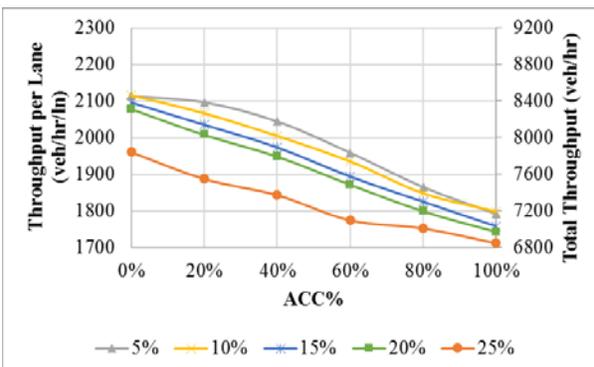


Figure II.3-1 - Throughput Trend with Increasing Autonomous ACC

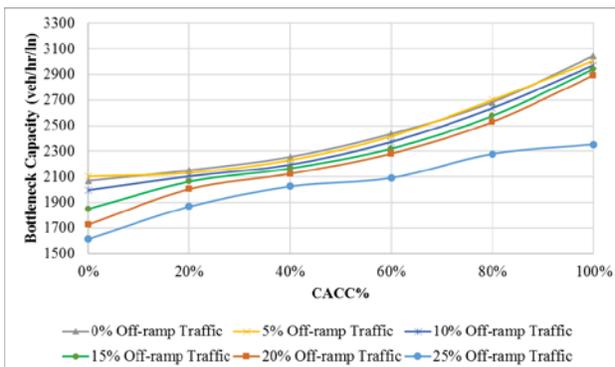


Figure II.3-2 - Throughput Trend with Increasing Cooperative ACC Market Penetration

Figure II.3-1 and Figure IV-10 show the contrast between the trends in achievable throughput per lane as the market penetration increases for autonomous (unconnected) and cooperative ACC systems respectively. The simulation scenario for these results was a section of four-lane freeway operating at its maximum achievable upstream throughput level, with a single exit ramp serving different exiting traffic volumes, ranging from none (the ideal case) to 25% of the mainline volume. The decline in achievable downstream throughput with

increasing use of ACC is in distinct contrast to the increase in downstream throughput with increasing use of CACC. This occurs because the ACC destabilizes the vehicle following control, while the CACC stabilizes it and enables the vehicles to be driven at shorter gaps.

The calibrated models of ACC and CACC vehicle following were applied to real-world freeway corridors. The initial calibration of the human driver model parameters was done for the SR-99 freeway corridor approaching Sacramento, CA from the south during the morning peak period. Figure II.3-3 shows the contour plots of traffic speeds along this corridor in the current base case, with no CACC vehicles, in the upper left corner of Figure II.3-3, followed by plots showing successively larger market penetrations of CACC, from 20% to 100% in 20% increments. The vertical axis of each plot represents the location along the corridor, the horizontal scale represents the time from 4 am to 12 noon during a weekday, and the colors represent the traffic speeds. As the CACC market penetration increases, the bottlenecks can be seen to dissipate while the corridor traffic volume remains the same as in the base case. This demonstrates the ability of CACC to reduce the traffic congestion that produces inefficient use of propulsion energy. Note that the 20% market penetration is actually worse than the base case. This occurs because the CACC system reverts to autonomous ACC when there is not an equipped vehicle in front of it, and at this low market penetration level most of the CACC vehicles have not arrived right behind another equipped vehicle, so they have been compelled to revert to the autonomous ACC mode of driving.

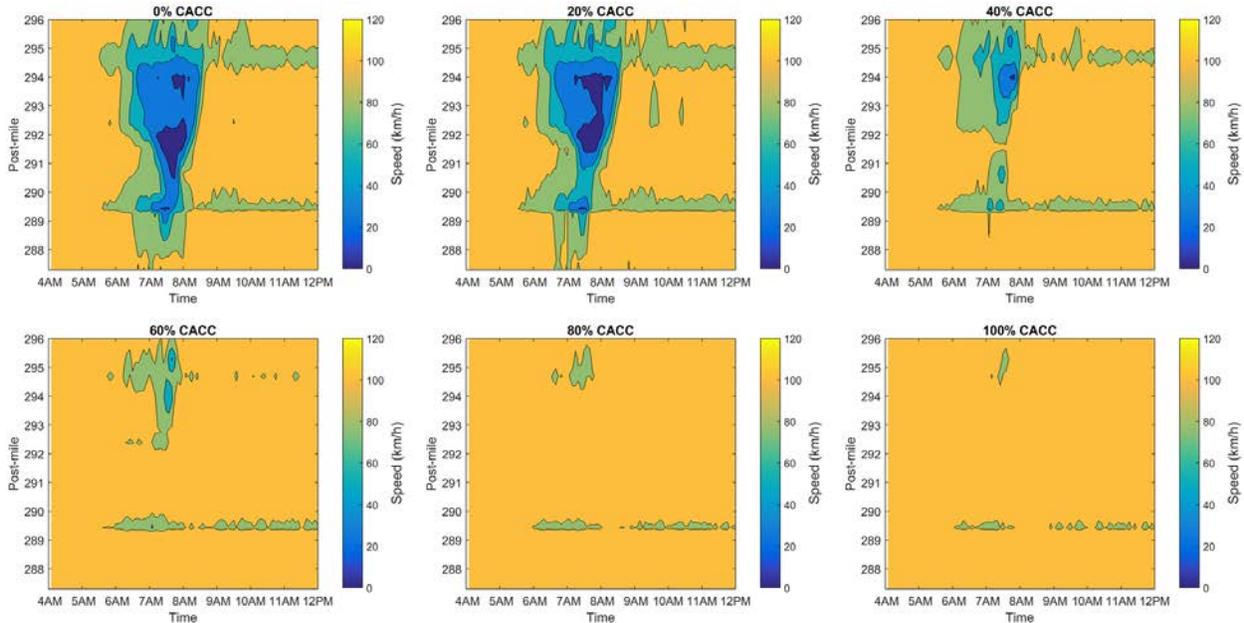


Figure II.3-3 - Speed Contour Plots for SR-99 Sacramento Corridor with All-Manual Driving and CACC at Market Penetrations from 20% to 100%

The effects of ACC and CACC on energy consumption can be visualized more clearly on contour plots for a simpler scenario, using a four-lane freeway section with a single on-ramp. Figure II.3-5 shows a fuel

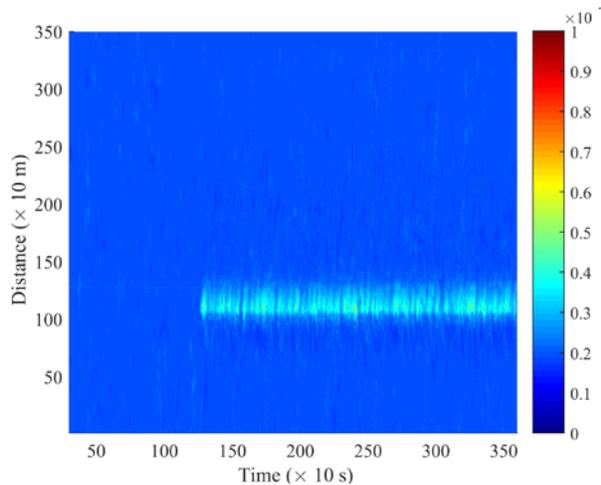


Figure II.3-4 - Fuel Consumption Contour Plot for 100% CACC Driving with On-Ramp Traffic Disturbance

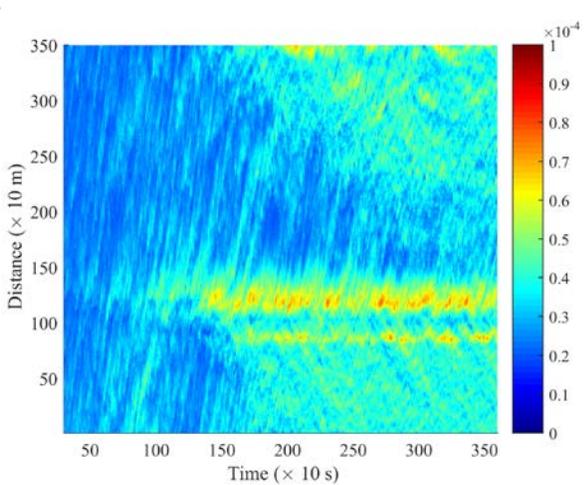


Figure II.3-5 - Fuel Consumption Contour Plot for 100% ACC Driving with On-Ramp Traffic Disturbance

consumption contour plot for a 3.5 km corridor for one hour of operation, with an upstream mainline approaching traffic flow of 1950 vehicles/lane/hour, approximately the maximum capacity for manual driving, plus an on-ramp volume of 600 vehicles per hour beginning after the first 20 minutes of simulation. Figure II.3-4 shows that when all the vehicles are using CACC the impact of the on-ramp traffic is negligible, but Figure II.3-5 shows that when all the vehicles are using autonomous ACC the fuel consumption increases significantly because of the unstable vehicle following.

There is a subtle trade-off between fuel consumption and maximum freeway throughput because when the usage of CACC is maximized and the traffic throughput is pushed to the maximum achievable by operating long strings of CACC vehicles, congestion can re-emerge, while the highway is handling a much higher traffic volume. This trade-off is shown in Figure II.3-6, which shows the downstream capacity of a freeway section increasing as the upstream input traffic increases, but with some flattening as congestion builds up (red curve), while the energy efficiency declines as that congestion increases (blue curve). Note that the vertical scale on the right side of the plot is showing energy savings toward the upper end (negative signs in fuel consumption signifying savings).

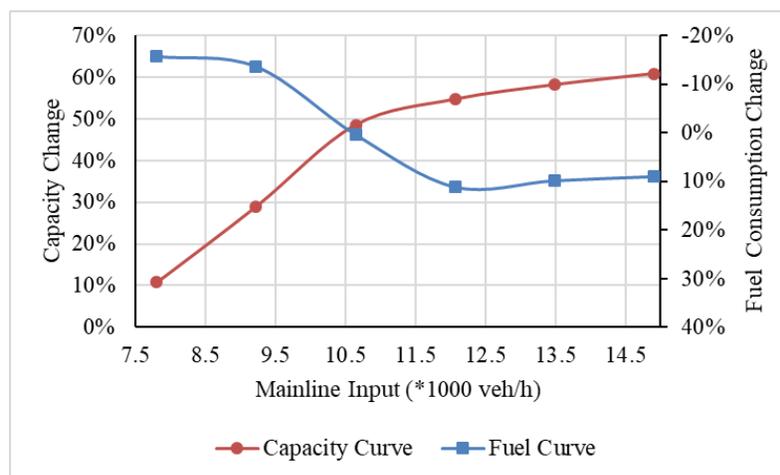


Figure II.3-6 - Trends in Downstream Freeway Lane Throughput and Energy Efficiency as Traffic Volume Increases

The simulations of energy efficiency effects for heavy trucks have been done for the I-710 corridor between Long Beach and downtown Los Angeles, which carries exceptionally heavy truck traffic from the major container port in Long Beach. For these simulations, the extra aerodynamic drag savings associated with operation of the trucks at shorter than normal gaps required some new simulation development work because the existing energy consumption estimation software does not have any provisions for capturing this effect. The energy consumption measurements from the Task 7A3.1 research were used to estimate the necessary adjustments to the normal fuel consumption estimates for the heavy trucks for the cases when the trucks were using CACC control to follow each other (based on the energy savings at the 1.2 s time gap that was most preferred by drivers in a recent PATH field experiment).

The I-710 corridor is a congested urban corridor, so the trucks are not able to operate continuously at high speeds. In order to estimate the energy saving potential of truck CACC, the simulations were conducted beginning with the current baseline traffic conditions, and the same travel demand for both cars and trucks was assumed after the addition of the truck CACC control. To estimate the maximum potential improvements from use of truck CACC, the analysis focused on the 100% market penetration case, and possible further work may consider intermediate cases. Based on the random arrivals of the trucks and no active coordination to facilitate the formation of CACC strings, about 76% of the trucks were driving independently or as the leader of a string (which means gaining no aerodynamic saving at the 1.2 s time gap setting), about 12% were in the first follower position and 4% were in a further follower position (the other 8% were stopped or braking, which means that they were not consuming propulsion energy). Therefore, only 16% of the trucks were eligible to receive aerodynamic drag benefits, and the average speeds along the modeled section of freeway ranged from about 33 mph in the base case to 40 mph with 100% CACC usage by the heavy trucks. At speeds this low the aerodynamic drag is not as large a contributor to total energy consumption as it is at free-flow highway speeds. The net result of these simulations was that the energy savings for all the trucks averaged about 0.5% attributable to aerodynamic drag reductions and about 2.5% attributable to the congestion reduction, smoothing out the speed profiles.

An option for possible further work in this task may consider a rural freeway corridor, with more sustained driving at full speed expected to lead to significantly higher aerodynamic drag savings.

Conclusions

Traffic microsimulations have been developed and applied to show the significant potential for energy savings through use of cooperative vehicle following automation (and the potential for adverse effects when the automation is non-cooperative). These tools have been used for specific scenarios in specific freeway corridors, but now that they have been developed and debugged they are available for use to represent a much wider range of CAV scenarios, including higher levels of automation.

When high percentages of the passenger cars on a freeway use cooperative vehicle following they can dramatically reduce congestion and increase the effective throughput of the highway. That smoothing of traffic flow disturbances produces significant energy savings. When heavy trucks use cooperative automation in congested urban corridors, their main energy saving benefit is attributable to the reduction of congestion and traffic flow disturbances.

Key Publications

1. H. Liu, S.E. Shladover, S.-Y. Lu and X. Kan, "Vehicle Fuel Efficiency Improvement via Cooperative Adaptive Cruise Control Operations", paper under submittal for review by *Transportation Research Part D*.

II.4 Impact of Connected and Automated Vehicles on Energy, and Mobility in a Metropolitan Area [Task 7A.1.3]

Joshua Auld, Principal Investigator

Argonne National Laboratory
9700 South Cass Avenue, Building 362
Argonne, IL 60439
Phone: (630) 252-5460
E-mail: jauld@anl.gov

Dominik Karbowski, Principal Investigator

Argonne National Laboratory
9700 South Cass Avenue, Building 362
Argonne, IL 60439
Phone: (630) 252-5460
E-mail: dkarbowski@anl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$630,000

End Date: September 30, 2017
DOE share: \$630,000

Non-DOE share: \$0

Project Introduction

Incorporating work from a previous, related project (9e-ANL), this task seeks to estimate the impact of Connected and Automated Vehicles (CAVs) on energy consumption and mobility in the context of a select large metropolitan area. A broad range of scenarios will be evaluated with varying market penetration rates of CAV technologies (determined in collaboration with the AOI2B team), vehicle technologies (e.g., hybrids and electric vehicles [EVs]), and CAV infrastructure. The evaluations will also include traveler behavior assumptions. The effects of the variations will be studied using a systems approach to allow examination of the complex interdependencies between technology, adoption, individual behavior, and network performance in the context of CAVs. To that end, the task will use the existing agent-based transportation modeling tool, POLARIS integrated with a vehicle energy model (Autonomie); the modeling tool, GREET; and existing detailed implementations of the Chicago tri-state metropolitan area. Collaborative developments proposed in other pillars will enable the study of CAVs in the context of an evolving complex transportation system, with shifting traveler behaviors, emergence of Mobility as a Service (MaaS) and its interaction with transit systems, and deployment of electric vehicle charging infrastructure. The analysis will differentiate between the various demographics and land uses to provide insights transferable to other areas.

Objectives

- Enhance the POLARIS simulation framework to simulate a wide range of CAV cases as specified by CAV7A1.1 and others
- Estimate the impact of CAVs on energy consumption, cost, and mobility in the transportation sector in a large metropolitan area (i.e., Chicago)
- Perform analyses in the context of evolving vehicle powertrain technologies

- Deliver case studies analyzing impacts of penetration rates, fleet compositions, land use, mobility services, and so forth on mobility and energy metrics

Approach

The approach taken to achieve the objectives of this project, which includes analyzing mobility and energy impacts from future CAV technologies, involved substantial development of the POLARIS framework relating to the traffic flow models, representation of vehicle agents, and implementation of resource allocation and optimization routines. The models of key traveler behaviors are incorporated into the POLARIS agent-based modeling framework in order to evaluate sensitivities of the various behaviors to potential changes under various Mobility Decision Science (MDS) scenarios. An overview of the improvements to the core POLARIS model is shown in Figure II.4-1. The primary tasks under this project over the last fiscal year involved:

- Development and implementation of updated mesoscopic traffic flow models sensitive to CAV impacts
- Implementation of vehicle as agents, including scheduling and operations within POLARIS
- Implementation of resource and scheduling constraints at the household level relating to vehicles
- Studies of the impact of vehicle-sharing within households
- Case studies demonstrating mobility and energy impacts under CAV scenarios.

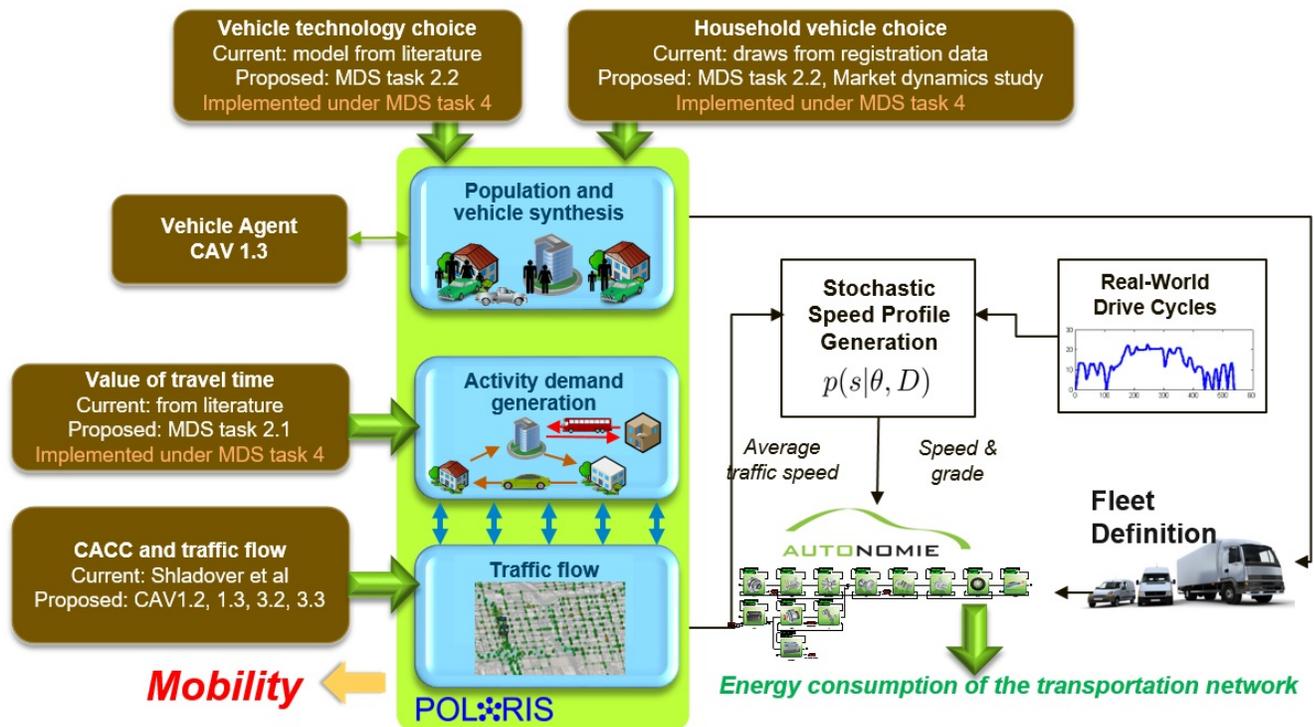


Figure II.4-1 - Collaborative POLARIS Transportation and Energy Modeling Process with CAV Improvements Highlighted

The project requires significant inputs from other tasks and pillars and was performed in collaboration with a number of other laboratories and universities. Texas A&M University has supported the work on updating the traffic flow models in POLARIS for CAV analysis. Lawrence Berkeley National Laboratory has provided inputs on traffic flow from CAV Task 1.2. Work performed under the MDS pillar includes behavioral models controlling time use and activity flexibility constraints for the Zero-occupancy Vehicle (ZOV) studies;

development of the vehicle and technology choice models that control the distribution of CAV-enabled vehicles in the studies; and the behavioral modifications for the implementation of the regional CAV impact study. Some of the optimization frameworks developed for incorporation into POLARIS resulted from Argonne LDRD funding through the Mathematical and Computer Sciences division. All models, except for some of the optimization frameworks, have been implemented in POLARIS as agent-based behavioral modules controllable through external parameter files as seen on the POLARIS GitHub repository. The POLARIS-Autonomie simulator with the updated behavioral modules in place was then used to analyze the energy impacts for scenarios relating to the effects of CAV technology on traveler value-of-travel-time (VOTT) savings.

Impact of CACC and Other Automation Technologies on Regional Traffic Flow

While corridor level microscopic simulations of CAVs in various modes of operation (e.g., isolated vehicles and Cooperative Adaptive Cruise Control [CACC]) is possible, their full impact can be only captured at the network level. However, most of the current state-of-the-practice in mesoscopic and macroscopic simulation tools cannot accurately capture the impacts of CAVs on congestion, emissions, and travel time reliability. The objective of this task is to develop such a capability in POLARIS by generating traffic flow fundamental diagrams for different compositions of vehicle technologies and road types, and using them to update the traffic flow models in POLARIS. The POLARIS traffic flow model takes advantage of traffic flow fundamental diagrams to calculate the speed of vehicles (depending on flow and density) in its traffic simulator; however, these diagrams depend very much on the composition of vehicle technology types on the road and also the road types. Figure II.4-2 shows the schematic of the work plan (note the tasks within the dashed red line are completed). We introduced a clustering method to capture traffic state over the space (network) and time. These clusters were used to reduce the number of required speed-density curves by focusing on just cluster heads rather than all detectors/sites. The candidate locations were identified and their geometries were created in the microscopic simulation framework. Several simulations were conducted for various market penetration rates of CAVs (considering both CACC and isolated automated vehicles [AVs]). To provide a more accurate representation of CACC and isolated AVs, two new modeling frameworks have been introduced and two papers were submitted on these models. Based on the simulation results, a series of speed-density curves were developed. Proposed next steps include incorporating the developed speed-density curves into the POLARIS traffic flow model. The outcomes of the proposed next steps could be evaluated at the mesoscopic level, more microscopic simulations could be conducted, and the results could be updated accordingly.

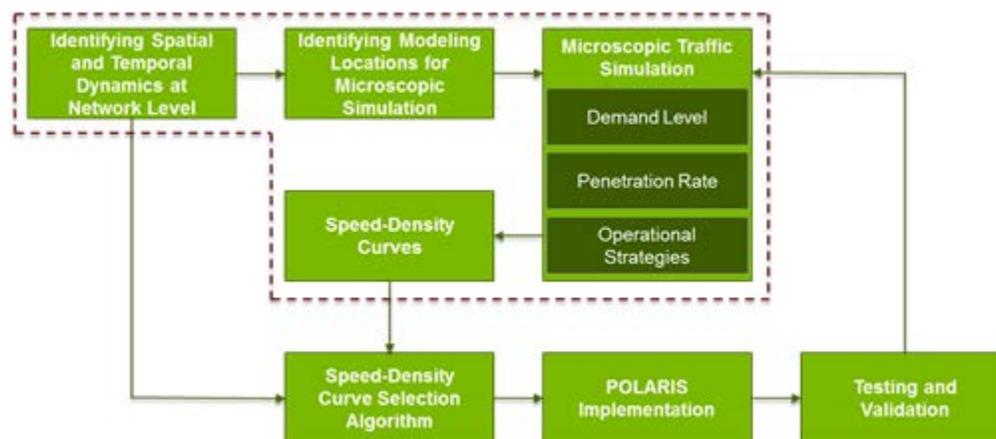


Figure II.4-2 - Traffic Model Updating Process with Completed Tasks Shown within the Dashed Red Line

Zero-occupancy Vehicle Travel Analysis and Within Household Vehicle Sharing

The ability to share AVs between individuals, either within a household in a private vehicle context or within fleets in a shared vehicle context, is a key aspect that allows for substantially altered travel patterns. Either

system would likely increase travel, not only through induced demand but also through vehicle dead-heading miles. The objective of this task is to study the energy consumption due to miles driven by ZOVs. As the first step to quantify such energy use, we developed an optimization algorithm to investigate the feasibility of using one AV to serve the travel needs of one household. Mixed integer programming was used to define the problems and Gurobi Optimization was used to solve them. Behavioral constraints on activity shifting were studied and implemented under the MDS pillar.

The objective function solved here was defined to maximize the number of household activities served while minimizing the number of ZOV trips and also minimizing the changes in activity start and duration. The constraints that were applied to the model guaranteed that changes to activity start and duration are within a threshold, while the time dependent travel times are considered when the vehicle travels between locations. Other constraints were applied to make sure just one vehicle enters and leaves the system. If it was not feasible for the vehicle to serve a trip, it was assumed that a taxi would be used. The focus of this task was on the possible generation of ZOV miles due to vehicle sharing; however the same framework will be applicable to additional CAV and MDS scenarios involving time, resource, and behavioral constraints.

Results

Using the updated POLARIS activity-travel simulator, a set of cases regarding the potential impacts for privately-owned CAV deployment were analyzed. The AV costs were modified from \$0 to \$15,000 to achieve the market penetration values specified in **Error! Reference source not found.** The VOTT reduction due to CAV and CAV technology purchase models developed under MDS Task 4 were applied to evaluate the results. The results in Table II.4-1 show that CAVS has some congestion relieving effects when no assumption of VOTT change is made (i.e., low rebound). However, as VOTT is reduced, travel increases occur. The worst case shows a 48% increase in vehicle hours traveled (VHT) and 45% increase in vehicle miles traveled (VMT), as well as indications of increased congestion. Overall, there is a 42% increase in fuel consumption in the high CAV case.

Table II.4-1 - CAV Deployment Mobility and Energy Results

Run	AV Penetration	VOTT Reduction	VMT (millions)	VHT (millions)	Avg. Travel Time (min)	Avg. Trip length (mi)	Fuel Use (MM gallons)
Base	0%	0%	268.0	8.17	23.4	11.79	4.85
0.2	36.1%	0%	291.2	7.86	22.2	12.50	5.34
0.3	75.5%	0%	292.0	7.96	22.5	12.73	5.32
1.1	10.1%	30%	306.5	8.37	23.7	13.38	5.62
1.2	36.1%	30%	324.6	9.04	25.5	14.21	5.94
1.3	75.5%	30%	337.7	9.64	27.3	14.82	6.14
2.1	10.1%	50%	319.2	8.74	24.7	13.99	5.85
2.2	36.1%	50%	357.8	10.45	29.9	15.77	6.55
2.3	75.5%	50%	387.4	11.92	34.5	17.40	7.05

Figure II.4-3 shows the geographic distribution of changes in fuel consumption for two cases using year 2040 vehicle technologies. The results show that changing the cost of CAV ownership while holding the VOTT fixed results in substantial fuel increases in outlying and more wealthy areas of the region, while holding the cost fixed and varying the VOTT shows a fairly uniform increase in energy and travel across the region, as expected, with the exception of the high density employment and activity areas. Individuals living in downtown and other urban core areas are already near optimal activity spaces and do not tend to engage in substantial amounts of extra travel regardless of the change in VOTT.

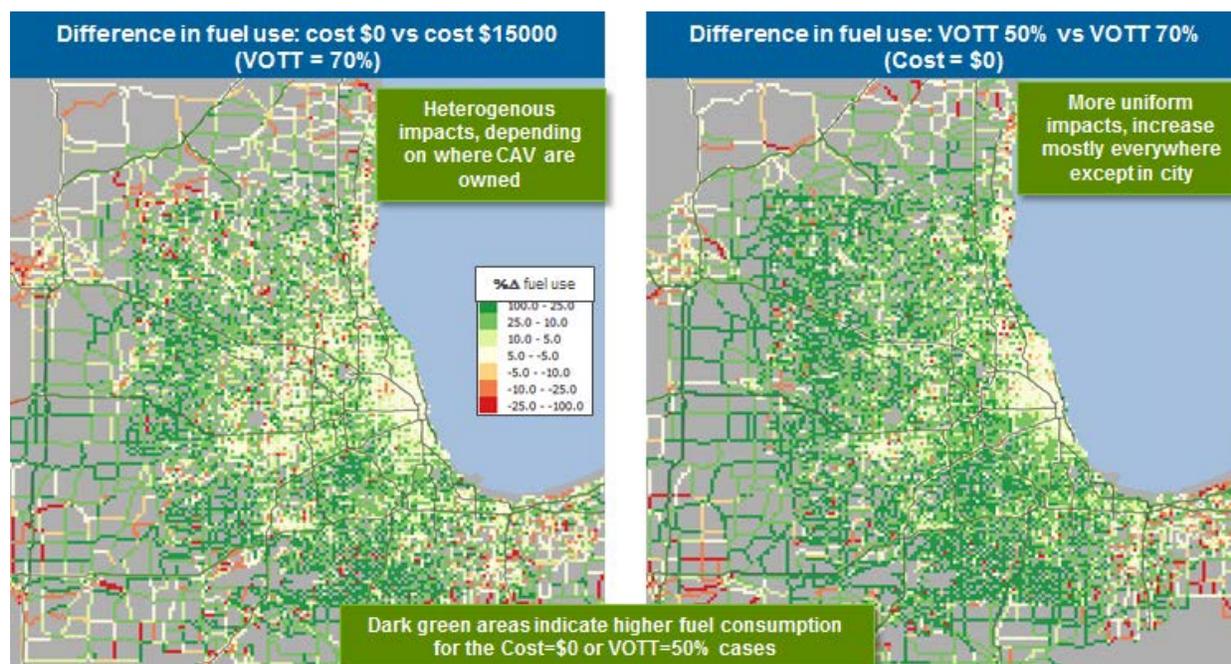


Figure II.4-3 - CAV Scenario Fuel Use Changes

An analysis was also conducted using the household vehicle-sharing framework on the potential of satisfying household trips by a single automated vehicle. Data from the Chicago Metropolitan Planning Organization (MPO) household travel survey data, which includes travel diaries of individuals in the Chicago region, was compiled, the algorithm was applied on selected households in the dataset, and five scenarios taking into account five levels of activity flexibilities (0, 5, 10, 15, 20 minutes) in start and duration were considered. Figure II.4-4 presents a sample of AV assignment to a three-member household for two scenarios, and Table II.4-2 reports the distribution of households by number of trips unserved by the single household AV.

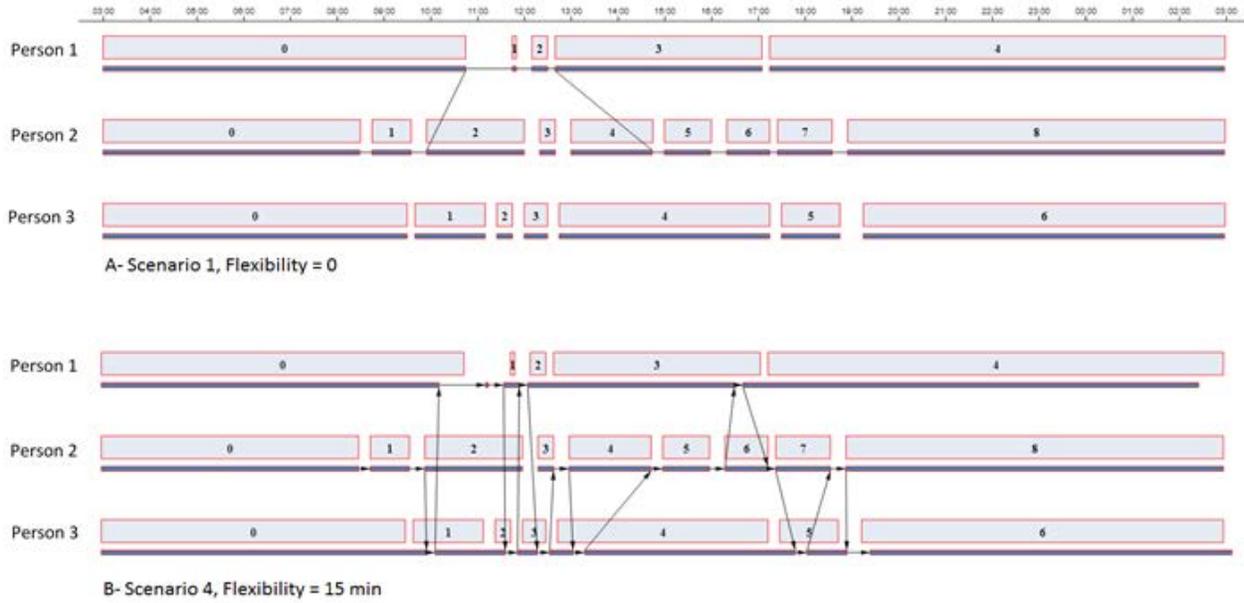


Figure II.4-4 - Two Scenarios Showing AV Assignment to Individuals in a Three Member Household

In Figure II.4-4, the prevalence of ZOV trips can be seen under scenarios with increased flexibility (ZOV trips show as diagonal trips between persons). As expected and is visible in the table, increased flexibilities allow more household to rely on just one vehicle for their daily activities. In high-flexibility scenarios, 57% of households in the observed database could meet all current travel needs with just one AV, versus 37% in a low-flexibility scenario. A more detailed model is under development that considers multiple AVs, while accounting for different costs associated with trips.

Table II.4-2 - Within-Household AV-Sharing Results

Unservd Trips	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	Flex = 0 mln	37%	Flex = 5 mln	43%	Flex = 10 mln	49%	Flex = 15 mln	53%	Flex = 20 mln	57%
0	1,220	37%	1,420	43%	1,609	49%	1,740	53%	1,887	57%
1	1,107	33%	1,053	32%	1,002	30%	972	29%	900	27%
2	661	20%	583	18%	496	15%	437	13%	394	12%
3	193	6%	171	5%	149	5%	115	3%	90	3%
4	78	2%	51	2%	36	1%	34	1%	30	1%
5	33	1%	24	1%	14	0%	8	0%	5	0%
6	13	0%	4	0%	1	0%	1	0%	1	0%
7	1	0%	2	0%	2	0%	2	0%	3	0%
8	3	0%	2	0%	1	0%	1	0%	0	0%
9	1	0%	0	0%	0	0%	0	0%	0	0%

Unserviced Trips	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	Flex = 0 min		Flex = 5 min		Flex = 10 min		Flex = 15 min		Flex = 20 min	
Total Unserviced Trips	3,603		3,110		2,683		2,395		2,130	
Reduction%	0		-14%		-26%		-34%		-41%	

Conclusions

The POLARIS model has been significantly enhanced in order to simulate the impact of various CAV technology scenarios. A fundamental update to the POLARIS traffic flow model will allow us to capture the impact of CAV technologies on traffic flow and congestion. Ongoing studies into household vehicle sharing and resource allocation allow for the analysis of future mobility options. The updated model has been used to explore potential impacts of CAV deployment and vehicle sharing, with demonstrated substantial energy impacts on the CAV cases depending on behavioral assumptions from the MDS pillar.

Key Publications

1. Auld, J., V. Sokolov, and T. Stephens. "Analysis of the Effects of Connected–Automated Vehicle Technologies on Travel Demand." *Transportation Research Record* 2625 (2017): 1–8.
2. Khajeh-Hosseini, M., A. Talebpour, M. Javanmardi, and J. Auld. "A Two-Stage Clustering Approach to Study Network Traffic Dynamics." Accepted for Presentation at the 97th Annual Meeting of the Transportation Research Board. Washington, D.C., January 2018.
3. Javanmardi, M., J. Auld, and O. Verbas. "Analyzing Intra-household Fully Autonomous Vehicle Sharing." Accepted for Presentation at the 97th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2018.

II.5 Modeling CAVs transition dynamics and identifying tipping points [Task 7A.1.4]

Brian Bush, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401-3305
Phone: (303) 384-7472
E-mail: brian.bush@nrel.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: January 1, 2017

End Date: September 30, 2017

Total Project Cost: \$130,000

DOE share: \$130,000

Non-DOE share: \$0

Project Introduction

Challenges to deployment of connected and automated vehicle (CAV) technologies extend beyond the vehicle and systems engineering challenges, and arise from a set of technological, economic, demographic, and regulatory issues. Informed observers of transportation markets and CAVs industry growth can develop intuition about the magnitude and implications of these challenges, but without analytic tools their understanding may make incomplete use of quantitative data, may be limited in its accounting for dynamic relationships across the system, and may be a poor basis for discussing possible actions. This presents a problem: limitations in shared understanding limits action. This task addresses the problem of limited actionable understanding by developing, applying, and communicating results from an analytic capability on the potential for large-scale adoption of CAVs and barriers to such adoption, making use of existing quantitative data and understandings of system relationships across the breadth of technological, economic, demographic, and regulatory issues.

Objectives

This task integrates with NREL's other CAVs impacts analysis contributions under SMART Mobility through closer examination of issues for successful large-scale deployment of CAV technologies and associated alternative travel paradigms, such as mobility as a service (MaaS). These technological, economic, demographic, and regulatory, issues could pose significant barriers. This task identifies and quantifies the circumstances and dynamics of potential transitions to future CAV success scenarios. Analysis emphasizes "tipping points" to large-scale adoption of CAVs and MaaS by highlighting the existing data that provides evidence for them, by performing sensitivity analysis around data inputs and by exploring policy scenarios that reach high penetration rates or provide additional benefits at lower penetration levels. The resulting analytic capability helps DOE and others to understand the potential for CAVs success scenarios and to plan their actions accordingly.

Approach

The approach of this task includes development of hypotheses about methodology and about CAVs deployment scenarios, collection of data about issues for CAVs deployment, and analysis using conceptual and functional modeling to test hypotheses. The functional modeling focused on the semi-quantitative representation of feedbacks related to CAVs adoption in a system-of-systems perspective and was embodied as a system dynamics simulation written in the STELLA programming language. Coordination with other project tasks and the identification of gaps in existing data and research were a key element of our approach. This approach enables us to meet our objective, as described in the sections below.

We coordinated the approach with other parts of the SMART Mobility project. We organized inter-laboratory teleconferences with Lawrence Berkeley National Laboratory (LBNL) and Oak Ridge National Laboratory (ORNL), served as testers and offered comments on the LBNL Whole Traveler Survey, and used the CAV Concepts Paper to inform our conceptual model of connected and automated vehicles and systems. Inter-laboratory coordination discussions focused on the Whole Traveler Survey and the vehicle choice model at ORNL. We identified potential future steps to align our work with their findings by incorporating data from the Whole Traveler Survey, sharing data about vehicle choice, and using our analytic capability to support pre-screening of Whole Traveler survey target regions. This coordination ensures that the best qualitative and quantitative information from across the SMART Mobility project will be readily included in our analysis when it becomes available.

Hypothesis Development.

Hypothesis development provides organizational structure for our methodological and analytic work, establishing priorities for the improvement of our understanding of CAVs opportunities. We developed and tested hypotheses about our analytic approach and about CAVs deployment scenarios. Development of methodological hypotheses structures decisions about model design. Development of CAVs deployment scenario hypotheses helps establish priorities among the many potential analytic questions. The current status of these hypotheses is summarized here:

Table II.5-1 - Hypotheses

Hypothesis	Test	Status
The model can be used to identify the conditions necessary to reach extremes of technology penetration in the CAV Concept Paper (Schladover and Greenblatt).	Model results	Confirmed
The interaction of overlapping “stage gates” (regulatory approval, consumer adoption, technology readiness, etc.) and the uncertainty in their time delays can be used to summarize the complex landscape of potential CAVs scenarios.	Model results	Partially confirmed
Synergies between technology pathways, CAVs concepts, and adoption behavior lead to multiple potential “end states.”	Model results	Pending
Freed time from driving (even constrained by operational design domain) is a strong driver of adoption. <i>Note: Hypothesis “partially confirmed” because time appears to be a moderate, not strong driver.</i>	Model results	Partially confirmed
The long term energy outcomes of various CAVs scenario concepts differ by half an order of magnitude.	Model results	Pending

Data Development.

Our approach to data development was to create a usable analytic model with plausible data, remain sensitive to data limitations, and avoid excessive time investment in data issues. Identifying data limitations and data improvement options was an important project outcome. Data collection relied on a series of searches of the public literature on CAVs under topics that included regulation, insurance, safety, state and local infrastructure investment, cost/benefit analysis, and effects on vehicle miles traveled. We also processed several primary datasets as needed for this task, including the National Household Travel Survey (NHTS) and the American Community Survey.

We used the raw NHTS to develop detailed data organized by activity, CAV concept, and population cohort. This informed a refinement to the organization of population cohorts in our modeling to align directly with population data in the NHTS, as shown in

Table II.5-2. We might modify these population cohorts once results of the Whole Traveler Survey and the next release of the NHTS are available. The table indicates the activities, concepts, and cohorts that we were able to populate using the NHTS. Processing the raw NHTS data enabled us to retain cross-tabular relationships that were available in the raw data but were not retained in summary tables, and to include details on modes (such as taxis and non-motorized) that were also dropped from summary tables.

For topics not covered in the NHTS, we identified and filled key data gaps. These included using data from the American Community Survey for selected demographics, the National Electric Vehicle Assessment study for certain variables about vehicle choice, and University of Texas Center for Transportation Research analysis for data on safety benefits.

Table II.5-2 - Initial Dimensionality of Population, Vehicles, and Activities

Population Cohorts	CAVs/Travel Concepts	Activity Purposes
Driver: prefer to drive themselves	Tele: telecommuting substitutes for travel	Work
AntiDriver: prefer not to drive themselves	Non-Motorized: pedestrian and bicycle travel	Shopping
NonDriver: unable to drive	CAVs 0-5 levels based on SAE International definitions:	Errands
Technophile: eager to adopt new technology	L0 Light-duty vehicle (non-CAV)	School
Technophobe: reluctant to adopt new technology	L0 Transit	Social
<i>Categories may be modified based on Whole Traveler Survey.</i>	L0 Taxi	Other
	L0 Eco (driver feedback)	<i>Categories are based on National Household Travel Survey</i>
	L1 Guided Busway	
	L1 Cooperative Adaptive Cruise Control	
	L1 Urban Eco Signal Control	
	L4 Automated Busway	
	L4 Semi Fixed Route Automated Shuttle	
	L4 Low Speed Automated Taxi	
	L4 Advanced Automated Taxi	
	L4 Urban Freeway Automated Driving	
	L4 Intercity Automated Driving	
	L4 Automated Highway	

Table Note: Categories have been carefully selected with the goal of simplifying dimensionality, at least initially. Population cohorts simplify from potential dimensions including demographics, ownership, driving preferences, and technology adoption preferences; CAVs concepts simplify from technology, functionality, and operational domain.

Conceptual and Functional Modeling.

Conceptual and functional modeling provided the analytic methodology to achieve task objectives of extending human intuition to a more quantitative platform that ensures consistency and accounts for feedbacks across a system. We developed a conceptual understanding of CAVs deployment by representing system relationships from the literature and expert opinion. We translated this into a functional “CAVs tipping point” model in systems dynamics using the STELLA simulation tool. This approach improves on human intuition in several ways: It accounts for feedbacks and shows relationships across the system, enabling development of self-consistent scenarios and development of consensus and shared understanding about what system elements are important and how they interact. It can be populated with either quantitative or semi-quantitative data with multiple sensitivities, respecting uncertainty and the level of detail available in the data.

Table II.5-3 - Status of Modeling Stakeholders

Stakeholder	Modeling Objective	Status	Potential Next Step
Travelers	Represent traveler preferences, value of safety, and time requirements	NHTS basis	Refine based on new NHTS and Whole Traveler Survey
Vehicle Owners	Compare alternative ownership models (e.g., MaaS)	Merged with Traveler	Refine based on ORNL Vehicle Choice model
Manufacturers	Include self-insurance during technology development and R&D investment	Initial	Interview subject matter experts. Consider adding strategic behavior (e.g., first mover dynamics)
Regulators	Represent potential for regulatory lag, and backlash due to safety concerns	Initial	Include data from proposed state legislation
Insurers	Represent need for data before underwriting, discounts and surcharges, vehicle-type-specific accident rates	Initial	Update use of incident data
Transportation Infrastructure Investors	Incorporate infrastructure constraints, investment, and development	Initial	Use infrastructure ratings and engineering standards to refine
Energy	Account for effects on energy use	Initial	Refine based on other SMART Mobility (particularly CAVs pillar) task outputs

Under the FY 2017 scope and funds, the CAVs tipping point model will be functionally complete in its initial scope and hypothesis-testing capabilities.

We used the CAVs tipping point model to test hypotheses and develop initial results, a selection of which are presented below.

Results

In order to examine the hypotheses summarized in Table II.5-3, we executed a sensitivity analysis on five key input parameters. We ran approximately 13,000 simulations that varied these parameters over plausible ranges of values. Additional scenarios explored the strength of feedbacks and casual influences in the model and identified sensitivities to other input parameters. The results show an initial mapping from transitions and barriers to points of leverage, which identifies likely end states, conditions for preferred end states, and strategies to avoid barriers. Figure II.5-1 illustrates possibilities for achieving such qualitatively different end states in terms of CAVs adoption and system-wide fuel use. At a more nuanced level, Figure II.5-2 and Figure II.5-3 demonstrate the interplay of behavioral parameters such as consumer preference or how consumers value their time versus financial parameters such as operating cost.

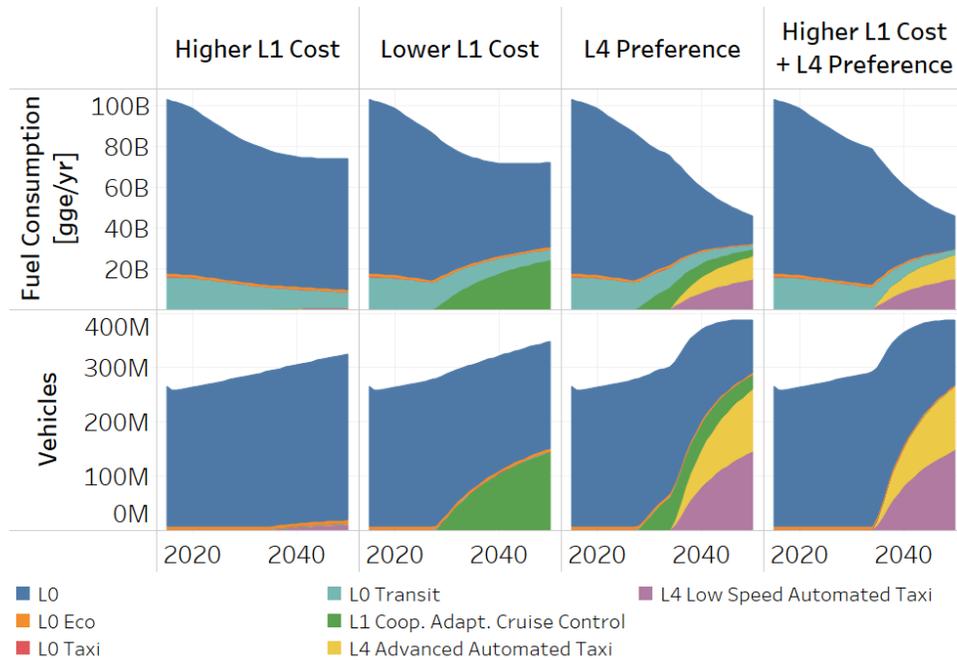


Figure II.5-1 - Comparison of simulations with higher and lower L1 costs and behavioral preference for L4 vehicles: The figure shows regimes with (from left) little CAVs adoption, L1 adoption, both L1 and L4 adoption, and L4 adoption. Fuel consumption without CAVs reflects vehicle efficiency improvements. The figure illustrates capabilities to explore different end states. (Source: NREL.)

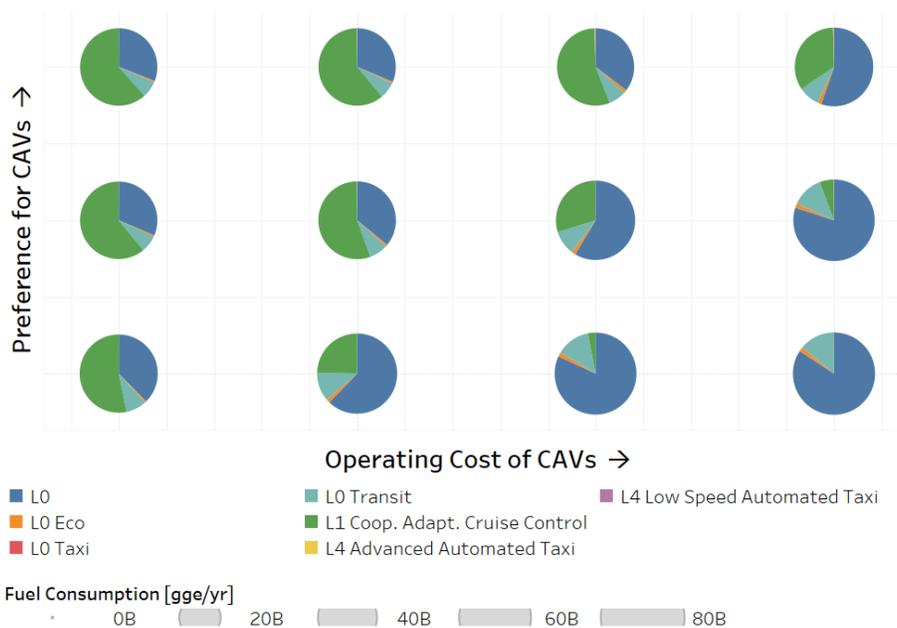


Figure II.5-2 - Sensitivity analysis of fuel consumption nationally in 2040 as a function of the operating cost for L1 and L4 CAVs technologies and consumer preference for using CAVs: These results show a rapid separation of end states dominated by CAVs (left and top sides of figure) versus end states where CAVs play a minor role (right bottom corner of figure). This highlights the need for quantitative understandings of both consumer preferences and also operating costs for CAVs technologies. (Source: NREL.)

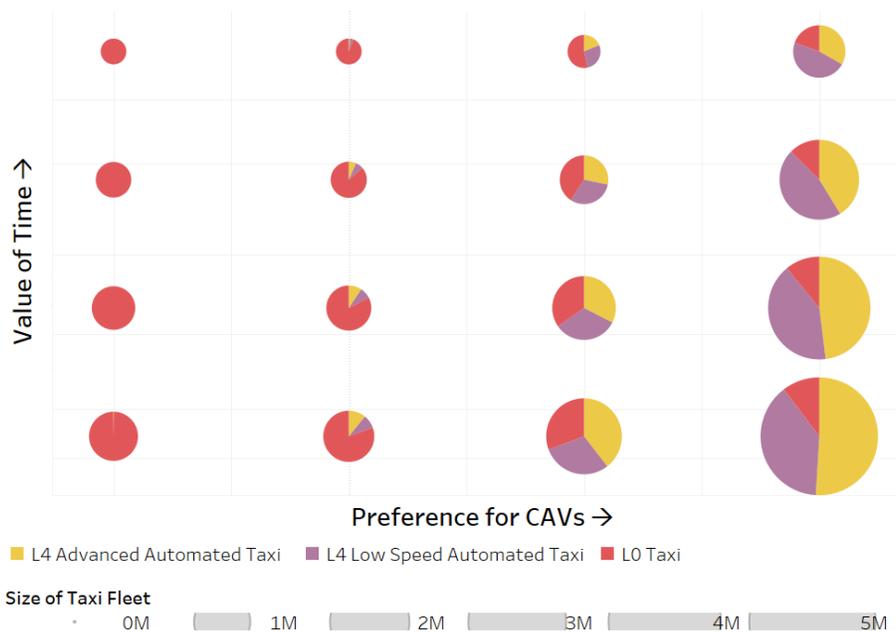


Figure II.5-3 - Sensitivity analysis of size of taxi fleet as a function of consumers' preference for using CAVs and the value consumers place on their time: These results suggest the possibility that the overall taxi or ride-source vehicle fleets may increase in scenarios where consumers show a substantial preference for the use of automated taxis (right side of figure), provided that such taxis are not disadvantaging in terms of travel time relative to non-taxis. (Source: NREL.)

Conclusions

This initial effort at conceiving, implementing, and preliminarily analyzing CAVs tipping-point dynamics using an analytic model demonstrates a capability to generate self-consistent CAVs-adoption scenarios for broad use by the CAVs stakeholder and analysis community. This capability can be applied to elucidate the relative influences of behavioral, cost, and technical parameters on CAVs adoption, thus highlighting where high value research might proceed to close substantial, influential data gaps. This work is exploring potentially significant feedbacks, points of leverage, and bottlenecks that may affect CAVs adoption, which includes (but is not limited to) consumer and manufacturer adoption choices. A candidate for possible further analysis would be to ingest upcoming survey data results, expand sensitivity analyses, explore adoption differences among urban areas, further test hypotheses, and embrace analysis of additional vehicle technologies, including medium- and heavy-duty CAVs.

Key Publications

The results of this task will be presented in a publishable journal article, initially formatted for peer review as a conference paper for the Behavior, Energy, and Climate Change conference.

II.6 Development and Application of Aggregate, Medium-to-longer term model of national regional travel and energy demand implications of CAVS [Task 7A1.5]

Paul N. Leiby, Principal Investigator

Oak Ridge National Laboratory
 P.O. Box 2008, MS 6036
 Oak Ridge, TN 37831-6036
 Phone: (865) 574-7720
 E-mail: leibypn@ornl.gov

David Anderson, Program Manager

U.S. Department of Energy
 Phone: (202) 287-5688
 E-mail: David.Anderson@ee.doe.gov

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 Total Project Cost: \$205,000

End Date: September 30, 2019
 DOE share: \$205,000

Non-DOE share: \$0

Project Introduction

Initial research for DOE and elsewhere has highlighted the large potential benefits new mobility technologies along with the high uncertainty regarding their aggregate longer-run impacts on national travel activity, energy use, and environmental outcomes. A range of study approaches is needed to improve our understanding of these issues, narrow the bounds of overall expected outcomes, and to determine the key determinants of travel demand, energy, and emission impacts of connected and automated vehicles (CAVs). This project complements detailed technological and spatial analyses underway, typically conducted for particular regions, cities, or roads and intersections in a computationally intensive framework, with a more aggregated top-down approach. Working from the other end of the problem, the ultimate goal of this project is a practical planning tool that, while more simplified in some dimensions, extends established market-based energy-economic frameworks for modeling travel demand and energy use to account for new mobility technologies, while still integrating key results and insights from detailed/ disaggregated studies. This will provide added perspective to the fundamental question of what technological and economic/behavioral factors drive overall travel/energy/emission outcomes at the national level. Moreover this can help explore and identify decentralized measures that could encourage medium and long-run evolution of the transportation energy market toward more beneficial overall national outcomes, while still enabling that market to achieve the efficiencies and large benefits that these technologies promise.

This work contributes to the SMART/EEMS goal to “understand [overall] energy efficiency opportunities” aggregating at system level, and accounting for behavior/economic responses. It will provide new insights on demand responses, and help suggest robust policies to guide travel and emission impacts.

Objectives

The objective is to develop and apply an aggregate, medium-to-longer-term model of national/regional travel, energy demand implications of CAVs. As an aggregate/integrative analysis this work will draw substantially on the progress of other SMART Mobility projects. In conjunction with the other 2B and 7A tasks, this project will use input from detailed spatially-explicit simulations and other vehicle and traffic simulations exploring the energy implications of specific CAV features, at the local to urban area scale. It will also draw on important contributions from the evolving Behavioral Science research including the Whole Traveler survey, consumer valuation of CAV travel time and EV use and charge behavior and urban scenario simulations. Outputs will be aggregating frameworks and simulations providing insights on overall travel and energy outcomes, allowing exploration for suitable and effective policy measures of any transportation network of interest.

Aggregate national estimates of travel demand response and energy use over the medium and longer term will include estimates of the impacts of automated shared mobility and heavy-duty/freight components.

This project supplements the work in AOI2B and providing an alternative approach to that used in task 7A1.3.

Approach

The novel methodology of this project is to develop an aggregate national model that integrates market and economic drivers, established theory regarding consumer/traveler economic behavior, and continuously improving data regarding travel activities and the energy efficiency performance of new technologies and practices. Specifically the approach will integrate the CAV technology/energy accounting frameworks developed by Wadud, MacKenzie and Leiby (2016) and others with the travel demand behavioral theory models of Small and Verhoef (2007) and others into a basic dynamic economic equilibrium model. Initial bounding-estimates of the aggregate energy impacts of CAVs in the literature were largely fixed-coefficient accounting analyses that were not yet representing important interactions, flexibilities and responses in technological and behavioral performance. This new approach uses an economic equilibrium framework to account for interactions between full travel cost (fuel, vehicle, time, other) and other attributes and constraints of importance to consumers and producers, and to estimate market outcomes regarding travel demand, vehicle efficiency, congestion and speed, energy use, and emissions. The model includes some reduced form representations of results from other technology and travel simulation models (e.g., related to CAV technologies and energy intensity, and travel activity and congestion), and can integrate key technological and behavioral results from detailed simulation models that are in development.

The approach involves sustained interaction and coordination with other CAV and MDS projects to establish major mechanisms to represent, parameter values and common scenario cases to be explored. It utilizes outputs from multiple CAVs tasks and MDS tasks, particularly related to the valuation and use of travel time. In FY 2018 the project will be combined with the group of “National Roll-up” modelers of NREL and ANL (combined 2B/7A1.5 CAVs tasks).

Collaborations with University of Maine and University of Washington helped in the development of the economic framework and the calibration of technological parameters. Implementation is in R and GAMS.

Results

In FY 2017 we completed the conceptual development for representing travel demand response in conjunction vehicle energy intensities and operating efficiencies, and its implementation in the base model for a single year and passenger light-duty vehicles. The equilibrium response modeling mechanisms were implemented and aggregate modeling approach tested. Significantly, the traveler/driver objective was extended to account for tradeoffs among consumption of travel (VMT), time, other goods, and leisure, subject to a travel production function and both budget and time constraints. This allows derivation of the demand for fuel economy and VMT (leading to demand for fuel), using a variant of the Parry & Small 2008 and Small and Verhoef 2007 approaches.

Presentation at AVS2017: 7/11/2017 “Decentralized Incentives to Promote Sustainable Outcomes with CAVs” Paul N. Leiby and Jonathan Rubin.

A completed paper: “Efficient Fuel and VMT Fiscal Incentives for Automated Vehicle,” July 31, 2017, was submitted for publication in Transportation Research Record, and will be presented at TRB 2018. This applies the above referenced driver objective and formulates a way to account for broad policy incentives, particularly fuel, VMT, and vehicle financial incentives. The approach economic conditions and incentives that allow efficient private behavior with CAVs while deterring the potential adverse social outcomes identified in recent literature (e.g., Wadud et al 2016, Stephens et al. 2016). The modeling approach follows, and extends for CAVs, the classic economic literature on traveler response based on utility and dual budget constraints on total income and time available. Related work under the MDS pillar will help benchmark modeled traveler behavior

through the estimation of time use and valuation using an empirical discrete choice framework that accounts for both the time and budget constraint.

Initial results explored the energy and net-benefit implications of the changing costs of travel, with changing energy and road-use costs. Illustrative results indicate greater potential gains in economic benefits for CAVs than conventional manual vehicles in cases where road use charges are applied, and at lower efficient road use charge levels.

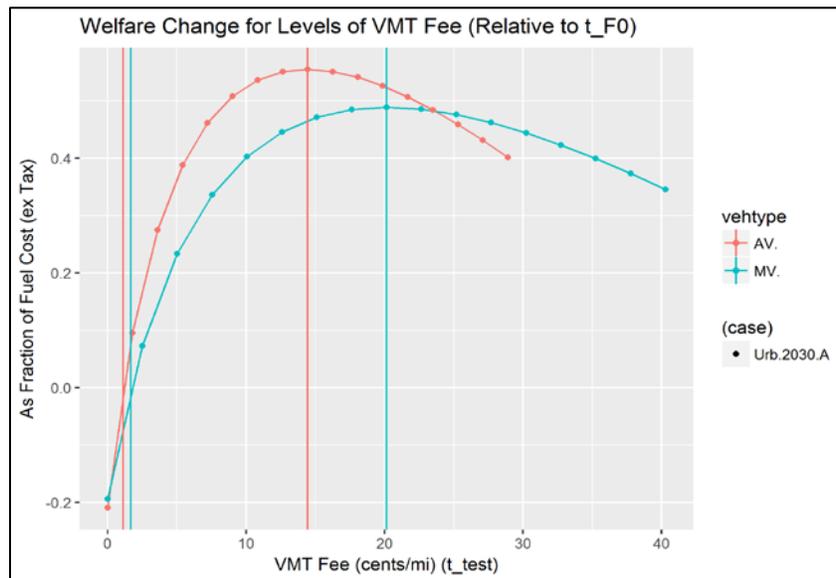


Figure II.6-1 - Economic Benefit Changes for Levels of VMT Charge suggest greater potential welfare gains for CAVs than conventional manual vehicles, at lower efficient road use charge.

A full report on model cases and initial model results (with new framework integrating technological factors and travel demand response) draft is in development (expected by late December 2017).

Planned FY 2018 work includes: Multiyear-dynamics, account for shared mobility business models, and explore range of outcomes and robust policies. Include improved technological efficiency estimates and travel demand response specification from results of other EEMS research.

Conclusions

Initial experiments show that accounting for endogenous travel demand response by households and endogenous fuel efficiency responses to economic signals leads to significantly different estimates of net aggregate energy use by CAVs. Indications are that accounting for economic equilibrium responses to changing costs and market incentives based on fuel use, VMT or vehicle purchases can improve our understanding of the range of potential aggregate energy and travel outcomes. CAV energy use and VMT can respond to changing economic costs and financial incentives in important ways that should be explored. Improvements in aggregate benefits (through expanding travel services while encouraging efficiency and discouraging congestion and low-value VMT) may be achievable, and it is hoped that an aggregate economic framework such as this one can be illuminating. Important issues to be explored are the implications of the changing non-price attributes of vehicle travel (notably valuations of travel time, convenience, and safety), and the implications of shared mobility, for passenger and vehicle travel demand (PMT and VMT).

Key Publications

1. Leiby, Paul N. and Jonathan D. Rubin (Univ. Maine) 2017. "Efficient Fuel and VMT Incentives for Automated Vehicles," October 31, 2017, with J.D. Rubin (U. Maine) in final review for publication in *Transportation Research Record*. (To be presented at Transportation Research Board 2018 Annual Meeting, January 2018).
2. Leiby, Paul N. 2017 "CAV Energy and Demand Decomposition at the Aggregated National Level" Draft Report, Oak Ridge National Laboratory, October, 2017.

II.7 Multi-Scale, multi-scenario assessment of system optimization opportunities due to vehicle connectivity and automation [Task 7A.2.1 – Subtask 1]

Dominik Karbowski, Principal Investigator

Argonne National Laboratory
9700 S Cass Avenue, Building 362
Argonne, IL 60439
Phone: (630) 252-5362
E-mail: dkarbowski@anl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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Non-DOE share: \$0

Project Introduction

Connectivity between a vehicle and other vehicles (V2V) or the infrastructure (V2I), as well as sensors provide information to the vehicle about its environment and future driving conditions. A vehicle with automated driving then uses that information to perform the mission with various objectives in mind: improved safety, increased mobility, greater comfort, better use of travel time, increased road capacity (e.g., platooning), etc. As a result, the way vehicles move is changing, impacting their energy efficiency. These changes can hardly be captured by common energy efficiency quantification procedures which evaluate vehicles on a limited set of “human-driven” driving cycles.

Automation and connectivity furthermore can be used towards eco-driving – in which energy-efficiency is another objective of the vehicle dynamics control – without compromising passenger comfort in terms of drivability and travel time. In parallel, vehicles feature an ever broader range of advanced powertrain technologies, from hybridization to transmissions with high number of gears, designed to improve the overall vehicle efficiency. It is uncertain how combining these two trends will impact energy efficiency improvements: will one cancel the benefit of the other, or will they add up? Will there be synergies to achieve by adopting a holistic approach that looks at both vehicle dynamics and powertrain operations? Will there be powertrain designs that achieve greater energy efficiency at lower cost only when coupled with eco-driving algorithms? What will be the impacts in the real-world, not just in the best case scenarios?

This project aims at tackling these challenging questions by designing eco-driving and energy management strategies for vehicles with advanced powertrain technologies, as well as developing a software framework to evaluate them in as many realistic scenarios as possible.

Objectives

- Estimate the energy saving potential of advanced powertrain technologies in the context of vehicle automation and connectivity.
- Evaluate the benefits of various eco-driving approaches when applied to vehicles with advanced powertrain technologies.
- Develop eco-driving and energy management strategies that control vehicle speed and powertrain cooperatively in order to provide maximum energy savings, especially for vehicles with advanced powertrain technologies.

- Facilitate the development of energy-saving automated driving algorithms by the industry and research community through model-based system engineering.

Approach

RoadRunner, a framework for CAV and energy-efficiency simulation

Modeling vehicles from an energy consumption point of view is typically done by providing the vehicle speed cycle as a function of time or distance to a backward-looking model or forward-looking model (where a modeled driver “presses” the pedals to follow the cycle) such as Autonomie. Such approach allows to use high-fidelity plant models as well as complex control strategies. However, modeling CAVs, and eco-driving in particular, requires altering drive cycles, which means an extra tool, and more importantly the impossibility of closed-loop control. On the other hand, traffic flow micro-simulators such as VISSIM or Paramics model the act of driving and the interactions between vehicles and between vehicles and the infrastructure. It is possible to run compiled models of the powertrain, but generally traffic flow simulators are not well suited for complex, powertrain-specific eco-driving algorithm development. As a result, we designed RoadRunner as a tool that would fill the gap between these two approaches.

RoadRunner is a simulation framework built upon Autonomie where multiple vehicles with full powertrain models and the interactions between the vehicles and their environment can be simulated. It is designed to allow the simulation of a broad range of driving situations, while facilitating the development of control strategies where the powertrain and the vehicle dynamics interact in a close-loop fashion.

RoadRunner simulates longitudinal movements of one or more user-defined vehicles along a user-defined route.

Figure II.7-1 shows the various stages of simulation and analysis in RoadRunner. The route attributes (such as position of traffic lights, grade, etc.) can be automatically extracted from a digital map (e.g., HERE) provided an origin and a destination. The user also defines which Autonomie vehicles to simulate and in which order. Presently when multiple vehicles are modeled, the lead vehicle follows speed limits and obeys intersection controls, and the other ones are following in a pre-defined order.

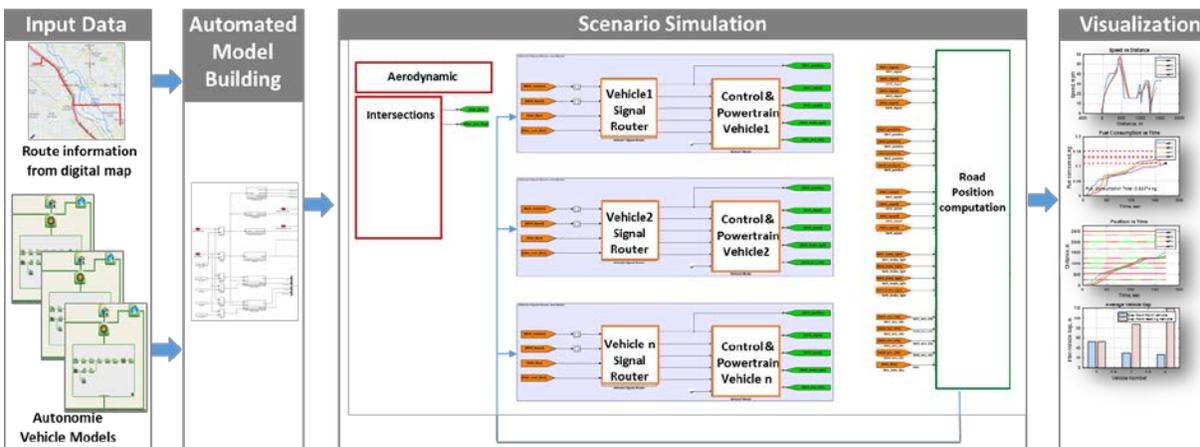


Figure II.7-1 - Diagram describing the RoadRunner workflow to simulate a CAV scenario

The automated building then creates the Simulink diagram for the scenario. Intersections are modeled either as a stop sign or traffic light, connected or not. Each vehicle is comprised of an uncompiled Autonomie plant model and supervisory controller, driver and/or longitudinal dynamics controller, with car-following and free-flow driving logic. An aerodynamics block computes the drag reduction coefficient based on relative position and inter-vehicle gap. Lastly, the position along the route is computed, and signal routers allow the proper flow

of information between the simulated agents (vehicles and intersections), so that each vehicle/driver only receives the information relevant to its position.

Roadrunner presently allows the simulation of human driving, platooning, cooperative adaptive cruise control, and connected intersection eco-approach for multiple vehicles.

Optimal control applied to eco-driving

In addition to the development of the simulation framework, this project also investigates novel approaches for eco-driving, in particular using optimal control theory. The control problem is to minimize the fuel consumption of a mid-size parallel HEV on a highway trip, with knowledge of grades and speed limits, while not compromising travel time. Vehicle speed and powertrain operations are therefore optimized together in a single formulation.

All fuel economy simulations are run using Autonomie plant models. The driver sets a desired speed v_{set} for the entire trip, and the automated vehicle control has to compute the engine and motor torques (T_e and T_m) as well as the gear while staying within speed limits. The road grade and speed limits are fully known to the vehicle controller and are piecewise constant, and free flow conditions are assumed, meaning the vehicle speed is not constrained by the speed of other vehicles.

The optimal control problem consists in minimizing $J = \int_0^{t_f} P_f + \lambda_E P_{bat} dt$, the weighted energy consumption (P_f : fuel power; P_{bat} : battery effective power) given initial and final conditions on speed v and position s . The Pontryagin Minimum Principle (PMP) states that the optimal solution minimizes the Hamiltonian $H = P_f + \lambda_E P_{bat} + \lambda_v \frac{dv}{dt} + \lambda_s \frac{ds}{dt}$ where λ_v and λ_s are called co-states. The PMP further provides dynamic equations for the co-states, and we can express P_f and P_{bat} as quadratic polynomials of gearbox input speed ω and respectively T_e and T_f . Newton's Second Law of Motion links $\frac{dv}{dt}$ to v and grade α . Previous works also demonstrated that the Hamiltonian is constant: $H(t) = H_0$. As a result, the optimal control can be fully computed for given λ_E , H_0 and λ_s . These parameters can be estimated when considering particular situations and the fact that they are constant (λ_E , H_0) or piecewise-constant (λ_s and grade are piecewise constant). The final stage in computing the optimal control for the trip is to take into account speed limit and component constraints into account, as well as identify the speed at the boundary of each road segment of constant speed limit and grade.

Results

Fuel consumption evaluation of eco-approach algorithms using RoadRunner

To illustrate RoadRunner, we developed a scenario with eco-approach and three conventional engine-powered vehicles: at the approach of a connected traffic light, the lead vehicle receives information about the current state and the next change of state.

The eco-approach algorithm features a 2-stage control logic that aims at minimizing energy consumption; it was inspired by literature. In a first stage, and at each time step, upper and lower bounds for vehicle speed are computed so that the vehicle reaches the intersection during a green phase, and within the speed limit. In a second stage, a cost function that balances safe distance with the preceding vehicle (if any), deviation from the upper bound speed (i.e., target speed computed in first stage) and vehicle tractive effort is minimized to find the commanded speed. A PID control then tracks the speed.

The baseline, non-connected driving strategy consists in aiming to drive at the speed limit. When starting from a stop, or when the speed limit increases, the vehicle follows a realistic acceleration profile; on the other hand when a speed reduction is necessary (lower speed limit, red light), the vehicle brakes following a deceleration profile, and in the case of a traffic light going yellow while the vehicle is close, a stronger deceleration is applied, unless the distance is too short (in which case the vehicle keeps on going). The acceleration and deceleration profiles are extracted from real-world driving data.

On a 3.4 mile route with speed limits of 25, 30, and 45 mph, 14 traffic lights and 2 stop signs, both control strategies were applied. 14% of fuel is saved in total by the eco-driving algorithm. Aerodynamic drag reduction due to reduced distances between the vehicles also contributes to this result. Furthermore, swapping the conventional powertrain vehicles for ones with a start-stop system reduces the fuel savings by nearly 2 percentage points. It should be noted that fuel savings may differ for other route scenarios.

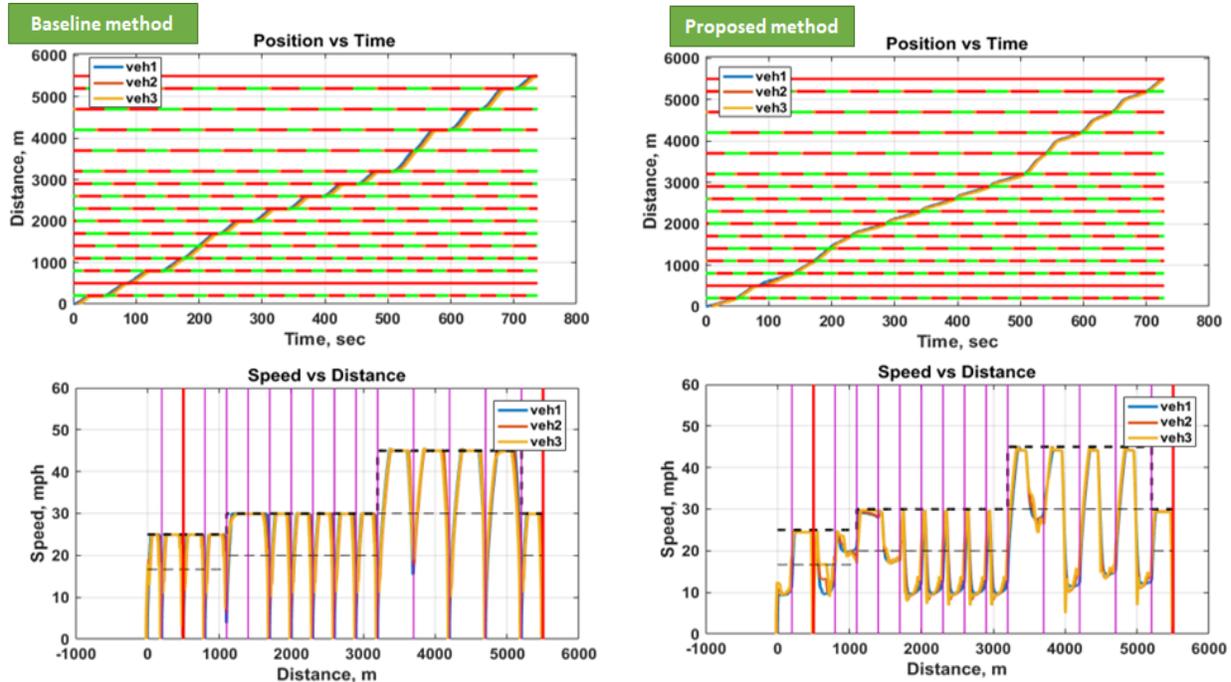


Figure II.7-2 - Speed trajectories (top) and speed traces (bottom) for a 3-car string of vehicles traveling on the same route, with no automation nor connectivity (baseline, left) and with eco-approach strategy enabled by connectivity (right)

Fuel savings of an eco-cruise control algorithm based on optimal control

The proposed algorithm relying on the PMP is applied to a 28-km example route with various speed limits and grades, illustrated in the Figure II.7-3. The speed set by the driver v_{set} is 25 m/s. The reference speed v_{ref} represents an average human behavior, with typical acceleration and deceleration when transitioning between speed limits, and v_{ref} is constant otherwise.

Three control strategies are compared. The baseline strategy is the default rule-based control in Autonomie, with a baseline driver. The “PT-PMP” strategy also uses the baseline driver speed, but the powertrain operations are optimized using PMP in the online controller. “DYN+PT-PMP” is the proposed eco-driving algorithm, which controls both the longitudinal dynamics and the powertrain. For “DYN+PT-PMP”, the solution was first computed offline, and resulting torque trajectories were then applied to Autonomie model, without close-loop feedback.

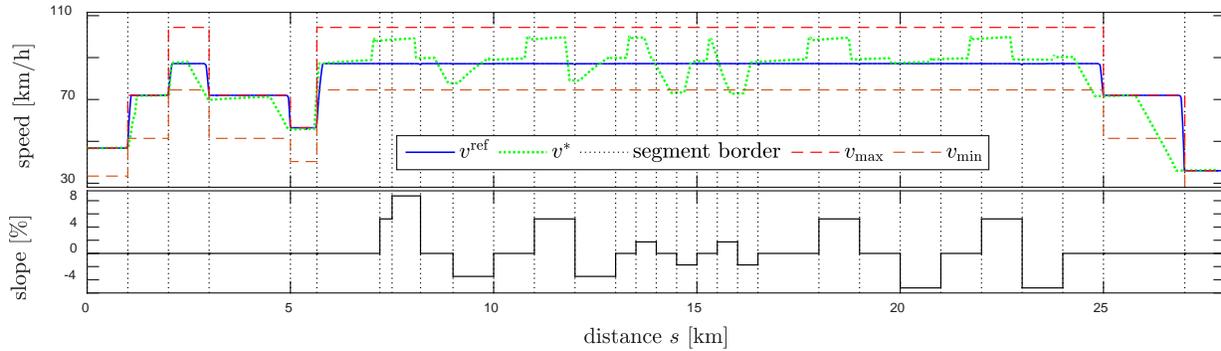


Figure II.7-3 - Reference speed, grade, speed limits for example route

Overall results for all three strategies are shown in Table II.7-1 below. The proposed algorithm (“DYN+PT-PMP”) results in approximately 6% fuel savings, whereas powertrain optimization alone (“PT-PMP”) yields less than half of that.

Table II.7-1 - Comparative evaluation of the three control strategies

	avg. speed [m/s]	num. of engine starts [-]	engine on duration [s]	avg. eng. efficiency [%]	ratio of fuel used for charging [%]	fuel [kg]	end SoC [%]	adj. fuel economy [L/100 km]	adj. saving [%]
Baseline	21.3	7	1069	33.1	22	1.024	59.29	4.95	-
PT-PMP	21.3	17	871	34.3	24	1.000	59.88	4.82	2.68
DYN+PT-OPT	21.2	18	507	34.4	14	0.917	51.75	4.68	6.02

Conclusions

- Developing and evaluating eco-driving strategies for CAVs will be facilitated thanks to RoadRunner, a simulation framework that simulates both higher fidelity powertrain models (from Autonomie) and the interactions between multiple vehicles and with the environment.
- Optimal control theory was successfully applied to the eco-cruise control problem, providing an algorithm that can find the most efficient speed and power split trajectories for an entire highway trip with grade variations and speed limit changes. It showed that on an example route, 6% fuel can be saved.
- A case study demonstrated how RoadRunner can be used for evaluating an eco-driving strategy. An eco-approach algorithm was applied to 3 vehicles with V2I connectivity on a short urban route with traffic lights, and the fuel savings for that particular scenario were estimated to be in the range of 14%.

Key Publications

1. Daliang Shen, Dominik Karbowski, Jongryeol Jeong, Namdoo Kim, Aymeric Rousseau, “Energy-Efficient Cruise Control Using Optimal Control for a Hybrid Electric Vehicle”, 30th International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium (EVS30), Stuttgart, Germany, October 2017

II.8 Multi-Scale, multi-scenario assessment of system optimization opportunities due to vehicle connectivity and automation [Task 7A.2.1 – Subtask 2]

Jackeline Rios-Torres, Principal Investigator

Oak Ridge National Laboratory
2360 Cherahala Boulevard
Knoxville, TN 37921
Phone: (865) 946-1542
E-mail: riostorresj@ornl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$364,000

End Date: September 30, 2017
DOE share: \$364,000

Non-DOE share: \$0

Project Introduction

This work will quantify the possible benefits due to improving traffic flow with Connected and Automated Vehicles (CAVs) in multiple scenarios for any given city or region including sensitivities due to different penetration levels and varying degrees of automation. This task will also seek to evaluate the sensing requirements and identify key development topics in this area related to enabling further optimization. It will also explore possible technical barriers on vehicle communication and bandwidth related to specific CAV functionality.

Objectives

Quantify the benefits due to improving transportation efficiency with CAVs in multiple traffic scenarios for any given city including sensitivities due to different penetration levels and varying degrees of automation.

Approach

Partner: University of Delaware

- Developing an optimal coordination framework for Connected and Automated Vehicles (CAVs). This framework has been developed with the aim to coordinate the vehicles on different traffic scenarios to ensure a smooth traffic flow, reducing stop-and-go operation. The scenarios include: merging on-ramps, intersections, roundabouts, speed reductions zones
- Developing a simulation framework to simulate mixed traffic, i.e., CAVs interacting with Human-Driven Vehicles. The optimal coordination approach for CAVs has been combined with the Gipps car following model that is used to represent driver behavior
- Performing simulations to assess the impacts of optimal coordination of CAVs considering different penetration rates and traffic conditions on a particular traffic scenario
- Integrating the optimal coordination framework with the VISSIM traffic simulator software to facilitate the simulation of interconnected traffic scenarios (e.g., a highway corridor, an urban neighborhood).

Results

We have investigated the impacts of full penetration of CAVs for different traffic scenarios. In addition, we have developed a simulation framework to study the impacts of gradual penetrations of CAVs on a merging on-ramp.

Impacts of full penetration of CAVs for different traffic scenarios

Merging on-ramp

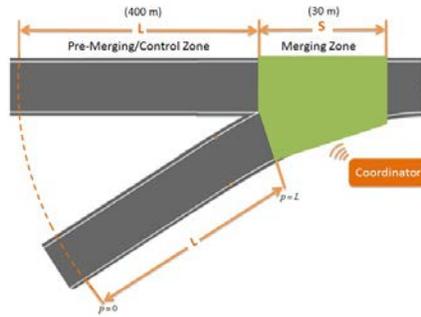


Figure II.8-1 - Simulated merging on-ramp

We simulated a merging on-ramp (Figure II.8-1) to assess the impact of optimal coordination of CAVs for different traffic conditions in two cases: a) 0% penetration (Baseline) and b) 100% penetration. We generated traffic scenarios assuming different entry volumes for 300 vehicles. For the baseline case we assumed that each driver behaves according to the Gipps car following model while the CAVs follow the optimization framework described in [6,8] (see key publications). We simulated the two cases under each traffic scenario and used the aggregated simulation data to capture the macroscopic traffic flow and density for both scenarios.

The plot in Figure II.8-2 shows that fuel consumption is reduced for all the simulated traffic conditions. For low traffic the fuel consumption is reduced by around 35%. The total fuel consumption varies significantly in the baseline case in medium and high traffic due to increased stop-and-go operation. The largest variations in the average traffic scenario is attributed to the fact that the vehicles still have some “freedom” to accelerate/decelerate as opposed to the case of high traffic where they are more “constrained” by the smaller headways and the predominant idling condition. In contrast, for the 100% penetration, the fuel consumption increases gradually for average traffic but it reaches an almost constant value again for heavy traffic. Note that for heavy traffic conditions, the percentage of fuel consumption reduction remains between 45% to 55%.

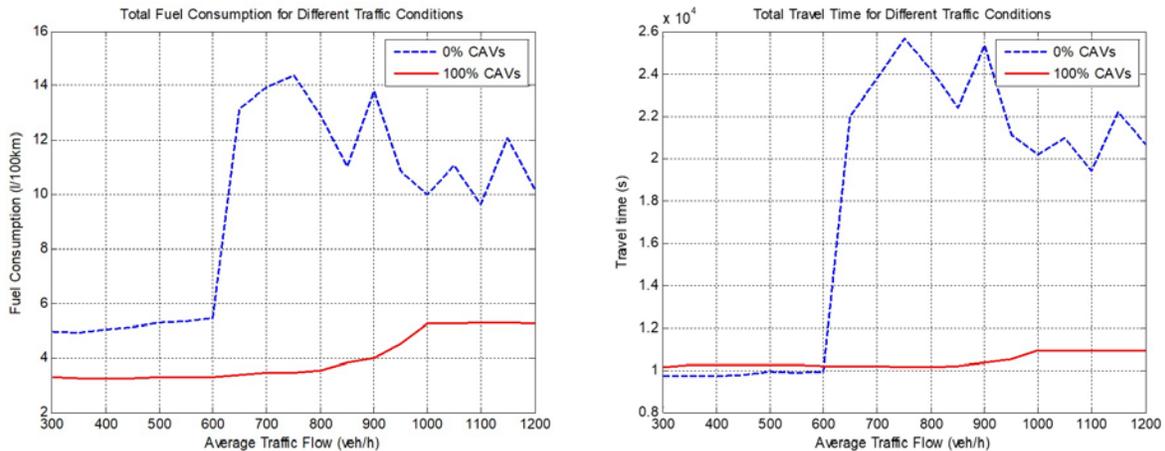


Figure II.8-2 - Fuel consumption and travel time for different traffic scenarios.

On the other hand, the total travel time (Figure II.8-2) remains very close for both cases in low traffic conditions but can vary widely in the baseline case for medium and high traffic compared to the 100% penetration case.

Roundabouts

We simulated a simple roundabout network in the traffic simulation software PTV VISSIM (Figure II.8-3).

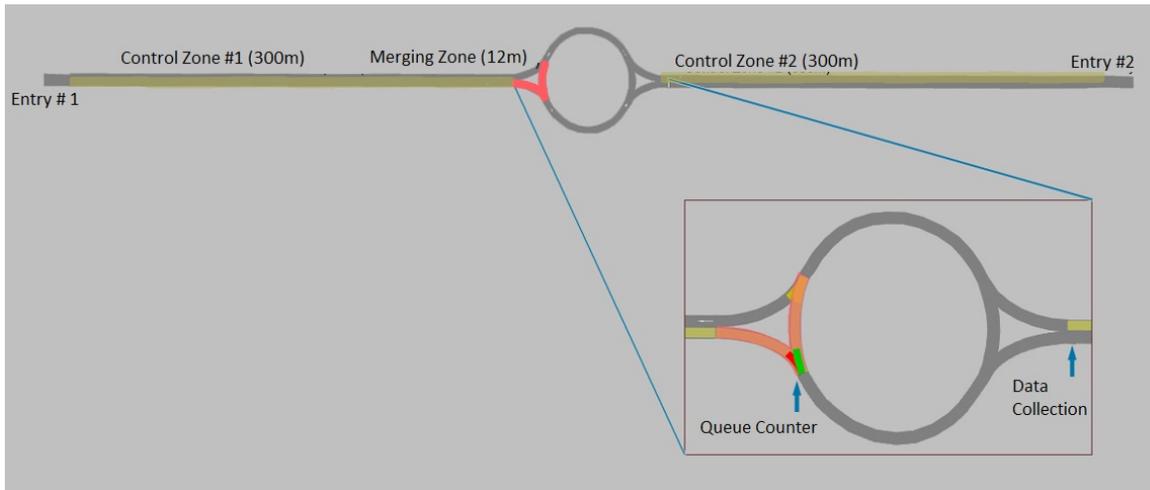


Figure II.8-3 - Simulated Roundabout

To evaluate the impacts of optimal coordination of CAVs for different traffic conditions, we created two scenarios: a) a network with 0% CAVs penetration (baseline) and b) a network with 100% CAVs penetration. In addition, to test the control effectiveness under different traffic conditions, a set of entry volumes varying from 300vphpl to 1000vphpl is investigated. The optimal coordination algorithm in [2,6] was implemented through the VISSIM API to represent the CAVs operation while the Wiedemann car following model is selected to represent the drivers' behavior in the baseline case. Every 60 secs, the aggregated data including travel time, volume, and queue are recorded for network performance evaluation.

Under low traffic, the headways between westbound traffic are generally large enough so that few eastbound vehicles need to stop to get into the roundabout. As entry volume increases, it is harder for eastbound traffic to

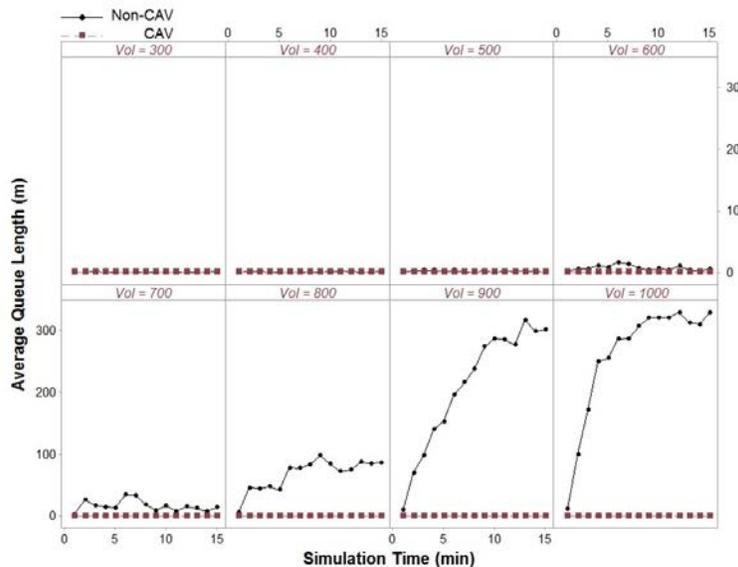


Figure II.8-4 - Average queue length of east bound traffic

find proper gaps to merge, resulting in a queue built up until the end of the simulation. With the proposed control algorithm, the network throughput was improved and the eastbound vehicles are able to merge into the roundabout without stops even with high circulating flow. As shown in Figure II.8-4, the queue length for eastbound traffic is eliminated with the proposed approach. Therefore, the total number of vehicles exiting the roundabout increases, leading to an improved roundabout capacity (e.g., 25% improvement with 1000 vphpl entry volume).

In addition, through vehicle coordination, the large variation in traffic conditions is minimized and the overall network travel time (Figure II.8-5) is improved significantly. As a result, under different traffic conditions, a 3% to 49% travel time savings is observed for the entire network. Furthermore, by eliminating vehicles' stop-and-go driving for eastbound traffic, transient engine operation is minimized, leading to direct fuel consumption savings as shown in Figure II.8-5.

Under low traffic levels, the needs for vehicle control inputs are limited due to relatively large headways between vehicles. With the increase of input volume, while traffic congestion is unavoidable for non-CAVs, the benefits of the proposed approach become more substantial. Note that, due to the size of simulated network, with high traffic level, not all non-CAVs are able to enter into the network, therefore, the travel time and fuel consumption calculation do not include these vehicles in the virtual queue.

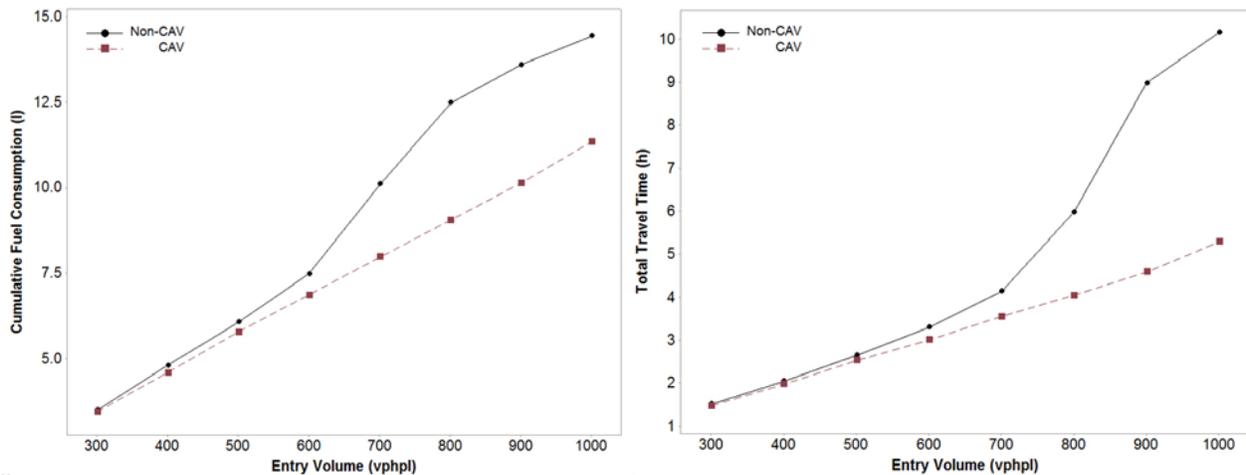


Figure II.8-5 - Total fuel consumption and total travel time vs. entry volume

Additional scenarios

The optimal coordination framework has been already applied to coordinate vehicles crossing an intersection and to optimize the performance of vehicles approaching a speed reduction zone on a freeway for a single random traffic flow scenario. In both cases the simulation results showed significant reduction in fuel consumption and travel time. The quantitative results are summarized in Table II.8-1.

Table II.8-1 - Quantitative results for intersection and speed reduction zone scenarios (comparison with respect to human-drivers)

Scenario	Fuel Consumption (%)	Travel Time (%)
Intersection	42.4%	37.3%
Speed Reduction zone	12% - 17%	28% - 32%

Impacts of partial penetration of CAVs on traffic flow

Since we seek to analyze the impacts of partial penetrations of CAVs, we combined the Gipps car following model and the optimal coordination control for CAVs proposed in [6,8] and developed a simulation framework for a merging on-ramp. Then, we simulated different penetration rates ranging from 0% to 100% for different sets of entry volumes. From the total number of vehicles, we select randomly which vehicle will be human-driven and which one will be a CAV.

For low entry volume, fuel consumption decreases as the penetration of CAVs increases. At 0% penetration the drivers on the ramp have to yield to the vehicles on the main road until a safe gap is available to merge (or a driver cruising on the main road may decide to decelerate and help creating the gap). This will eventually create a queue on the ramp with frequent stop-and-go driving patterns and, therefore, increased fuel consumption. In contrast, for full and partial penetration rates there are significant savings in fuel consumption as the vehicles cooperate to merge smoothly without stopping on the ramp. In particular, for full CAVs penetration the savings can vary from 45% to 47%.

For medium and high traffic volumes, total fuel consumption is reduced by 20% to 60% only with 100% penetration of CAVs. In the partial penetration scenarios, the CAVs following a human-driven vehicle are constrained by the random acceleration/deceleration choices of the driver and the lack of communication, so they will need to rely on their own estimations (through sensors) to ensure a collision-free trajectory. This implies that the CAVs will be adversely affected by the stop-and-go driving of the human-driven vehicles when attempting to merge and will be required to perform harder acceleration/deceleration maneuvers to ensure safety resulting in consuming more fuel. Ongoing work is exploring whether it is possible to account for human-behavior when optimizing the CAVs operation so that benefits in fuel consumption can also be realized with partial penetration of CAVs.

To analyze how the traffic evolves as CAVs gradually penetrate the scenario under analysis, we used aggregated traffic data collected from the simulations to plot the traffic flow vs density for different CAVs penetration values. Figure II.8-7 illustrates the flow-density plots for low CAVs penetrations (0%, 10% and 30%). In the baseline case (0%), the traffic flow is scattered and mostly concentrated below 1500 veh/h while the road utilization remains at low values. At low CAVs penetrations, i.e., 10% and 20%, the data points representing congested traffic become even more scattered while the road utilization starts increasing. The increased instability of the traffic flow at low penetrations is attributed to the fact that CAVs are not able to accurately estimate the behavior of human-driven vehicles and need to constantly self-adjust their controls or over-write their computed optimal inputs to ensure a collision-free trip. This implies that CAVs will be more prone to sudden decelerations that will be reflected in the downstream traffic.

At higher penetrations (50% and 80%) the data points are still scattered on the plot (Figure II.8-7). However, the traffic becomes more stable and the data points start concentrating at higher traffic flows (>500 veh/h) and higher densities (>100 veh/km) given that more CAVs are on the road communicating with each other and coordinating to merge. At full penetration (100%), and for average traffic values less than 1500 veh/h the traffic flows freely, i.e., there is not congestion. As the traffic start reaching the road capacity, some congestion

can still occur (at high traffic flows and densities), but in general the flow-density diagram shows a significant reduction in the traffic flow variations compared to the mixed traffic conditions.

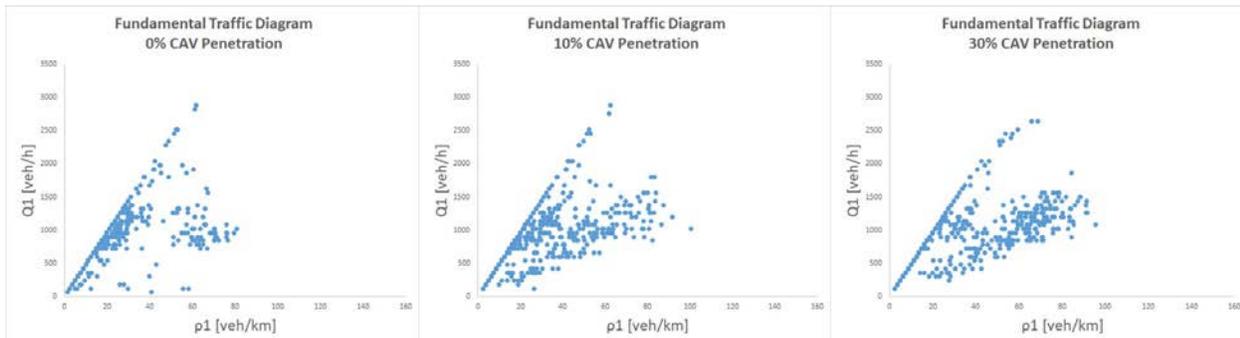


Figure II.8-6 - Flow-density diagram for lower CAVs penetration

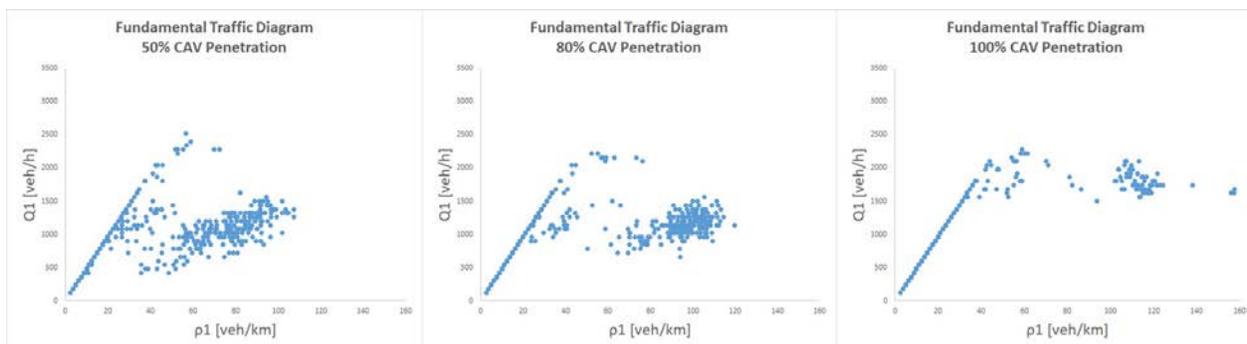


Figure II.8-7 - Flow-density diagram for higher CAVs penetration

Conclusions

In this project, an optimal control approach has been developed to achieve optimal coordination of CAVs. This developed modeling framework for CAVs can be adapted to different traffic scenarios and has potential for real time implementation given that it is solved in an analytical way, obtaining a closed-form solution. The developed coordination approach, has been used to investigate the impacts of full penetration of optimally coordinated CAVs for different traffic scenarios: merging on-ramps, roundabouts, intersections and speed reduction zones. Overall, it has been demonstrated that *full penetration* of CAVs can contribute with significant savings in fuel consumption and travel time and mitigation of traffic congestion. Additionally, preliminary simulations have shown that *partial penetrations* of optimally coordinated CAVs can contribute with more stable traffic patterns and, only for low traffic flows, they can help reducing the fuel consumption. Ongoing work include the analysis of the effects of gradual CAVs penetration for additional traffic scenarios (Using a traffic simulation software), as well as interconnected scenarios (e.g., a highway corridor with interconnected on-ramps and off-ramps) and, whether CAVs can be used to have indirect control of human-driven vehicles with the aim to achieve reduced fuel consumption and more stable traffic patterns in mixed traffic conditions.

Key Publications

1. Rios-Torres, J., and Malikopoulos, A.A., "Partial Penetrations of Connected and Automated Vehicles and its Influence on Fuel Consumption and Traffic Flow" (in preparation)
2. Zhao, L., Malikopoulos, A.A., and Rios-Torres, J., "Optimal Control of Connected and Automated Vehicles at Roundabouts"

3. Malikopoulos, A. A., Hong, S., Lee, J., and Park, B., "Optimal Speed Control of Automated Vehicles at a Speed Reduction Zone," *Transportation Research Part C*, 2017. (in review)
4. Malikopoulos, A.A., Cassandras, C.G., and Zhang, Y.Z, "A Decentralized Energy-Optimal Control Framework for Connected Automated Vehicles at Signalized-Free Intersections," *Automatica*, arXiv:1602.03786, 2017. (provisionally accepted)
5. Rios-Torres, J., and Malikopoulos, A.A., "A Survey on the Coordination of Connected and Automated Vehicles at Intersections and Merging at Highway On-Ramps," *IEEE Trans. Intell. Transp. Syst.*, Vol. 18, 5, pp. 1066-1077, 2017.
6. Rios-Torres, J., and Malikopoulos, A.A., "Automated and Cooperative Vehicle Merging at Highway On-Ramps," *IEEE Trans. Intell. Transp. Syst.*, Vol. 18, 4, pp. 780-789, 2017.
7. Zhang, Y.Z, Malikopoulos, A.A., and Cassandras, C.G., "Decentralized Optimal Control for Connected and Automated Vehicles at Intersections Including Left and Right Turns," *Proceedings of the 56th IEEE Conference on Decision and Control*, 2017.
8. Rios-Torres, J., and Malikopoulos, A.A., "Impact of Connected and Automated Vehicles on Traffic Flow," *Proceedings of 2017 IEEE 20th International Conference on Intelligent Transportation Systems*, 2017. (to appear)
9. Zhang, Y.Z, Cassandras, C.G., Malikopoulos, A.A., "Optimal Control of Connected Automated Vehicles at Urban Traffic Intersections: A Feasibility Enforcement Analysis," *Proceedings of the 2017 American Control Conference*, pp. 3548-3553, 2017.
10. Hong, S., Malikopoulos, A. A., Lee, J., and Park, B., "Development and Evaluation of Speed Harmonization using Optimal Control Theory: A Simulation-Based Case Study at a Speed Reduction Zone," in *96th Annual Meeting Transportation Research Board*, 2017.
11. Rios-Torres, J., and Malikopoulos, A.A., "Connected and Automated Vehicle Merging at Highway On-Ramps," in *96th Annual Meeting Transportation Research Board*, 2017.
12. Rios-Torres, J., and Malikopoulos, A.A., "Energy Impact of Different Penetrations of Connected and Automated Vehicles: A Preliminary Assessment," in *Proceedings of the 9th ACM SIGSPATIAL International Workshop on Computational Transportation Science*, 2016.
13. Zhang, Y.Z, Malikopoulos, A.A., and Cassandras, C.G., "Optimal Control and Coordination of Connected and Automated Vehicles at Urban Traffic Intersections," *Proceedings of the 2016 American Control Conference*, pp. 6227-6232, 2016.

II.9 Enabling Electrification of Connected and Automated Vehicles [Task 7A.2.2]

Zonggen Yi, Principal Investigator

Idaho National Laboratory
2525 Fremont Ave
Idaho Falls, ID 83415
Phone: (208) 526-4293
E-mail: zonggen.yi@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2017

Total Project Cost: \$230,000

DOE share: \$230,000

Non-DOE share: \$0

Project Introduction

Tremendous work is being performed to electrify powertrain systems and the transportation system. Meanwhile, recently most automakers and some high-tech companies, e.g., Google, Uber, etc., are focusing on implementing autonomous driving technology. They are trying to put forward the real-world application of this technology. Furthermore, the automotive OEMs, e.g., Tesla and GM, etc., are combining autonomous driving technology with electric vehicles. Car-sharing or car-hailing companies plan to use both electric vehicles (EVs) and autonomous driving in their transportation network. Self-driving technology is an important aspect to improve their service quality and reduce operation costs. Electrified vehicles can help to improve the energy efficiency. These two trends will work together to improve the intelligence and sustainability of transportation system in the coming future.

The introduction of autonomous driving technology would remove the challenge of co-locating charging infrastructure with driver destinations and presents a driver-free method for EVs to reach nearby charging stations. This will significantly change the charging behavior of electric vehicles. EV driver will no longer need to be present at charging stations for charging actions. Automated EVs can drive to nearby charging stations to perform charging actions by themselves when necessary. Meanwhile, connected vehicles technology is emerging to make real-time connections between vehicles and infrastructure networks. Electric vehicles will have the capability to sense and obtain pertinent information from nearby charging station networks and then calculate the corresponding costs and availability for charging. This information will be very helpful for real-time, optimal and sustainable charging decision-making for electric vehicles.

With the emerging of electric vehicles and autonomous driving technologies, the demand for autonomous charging decision making is critical to improve the sustainability of charging for future autonomous electric vehicles, including the personal and shared vehicles. The development of autonomous charging decision making aids in understanding the driving and charging behavior in future autonomous transportation system. This is of importance to study the energy benefits of usage of autonomous electric vehicles. Idaho National Laboratory has abundant real world data and experience in electric drive system and its energy consumption and charging behavior. INL takes advantage of these valuable asset to improve the future charging decision making system of connected and autonomous electric vehicles and evaluate their potential energy impact.

Objectives

This project aims to evaluate the energy impact of electrified connected and automated vehicles under optimal charging decision-making strategies. In order to achieve this goal, this project is to develop data-driven and optimization based methodology for charging decision-making for electrified CAVs and validate proposed

models with real-world data from conventional vehicles and PEVs. The developed models also aim to provide the algorithmic capability for agent based transportation simulation platform to simulate system level driving and charging behavior of connected and automated electric vehicles.

Approach

Optimal charging decision making framework has been studied from two scenarios: personal connected and automated electric vehicles (CAEVs) and commercial CAEV fleet. This framework aims to provide charging strategies, i.e., the choice of charging station and the amount of charged energy, by considering constraints from potential itineraries and existing charging infrastructure. In order to achieve this, the following two technical approaches are utilized:

Data driven methods are proposed to construct the high-resolution energy consumption prediction model. The realistic traffic and temperature conditions are involved to predict a more accurate energy consumption for high fidelity simulation. The EV project and New York Nissan Leaf taxi data in Idaho National Laboratory are analyzed to obtain the energy consumption prediction models for personal and commercial vehicles, respectively. High-resolution energy cost prediction is the fundamental of optimal charging decision making.

Advanced mathematical optimization technique is applied to establish the optimal charging decision framework. This approach helps CAEVs to plan the energy-efficient routes and do charging decision making automatically. The proposed optimization models aim to reduce the trip energy consumption and charging cost during an itinerary, e.g., monetary cost and energy cost traveling to charging stations.

By taking advantage of introduced methodology, multiple scenarios assessments have been performed by using real world travel itinerary dataset, e.g., Chicago travel dataset and New York Taxi dataset. These assessments include the potential energy saving and benefits of autonomous driving for electric vehicles, energy impact of optimal charging decision making for CAEVs under realistic conditions, etc.

Results

Optimal Charging Decision Making for Personal Connected and Automated Electric Vehicles

Data Driven Energy Consumption Model

Energy consumption data of Nissan Leaf in the EV project is analyzed to construct the energy consumption behavior. The results are illustrated in Figure II.9-1 and Figure II.9-2. This is a stochastic energy consumption prediction framework in order to describe the uncertainties of energy cost with regard to average vehicle speed.

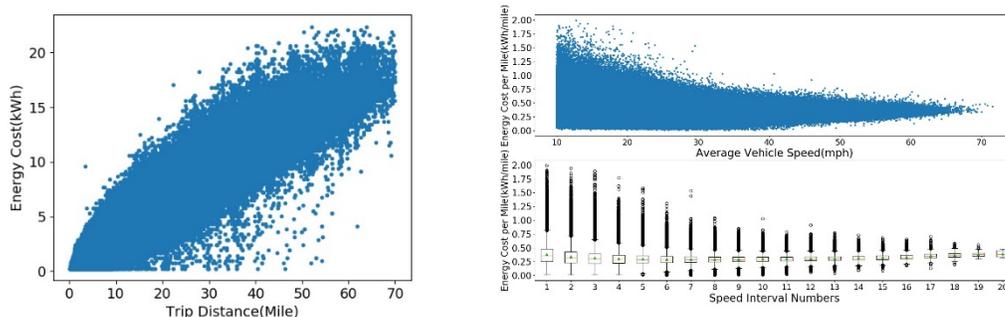


Figure II.9-1 - Left: Energy consumption with regard to trip distance; Right: Energy cost per mile with regard to average vehicle speed and the corresponding box-plot for uncertainties

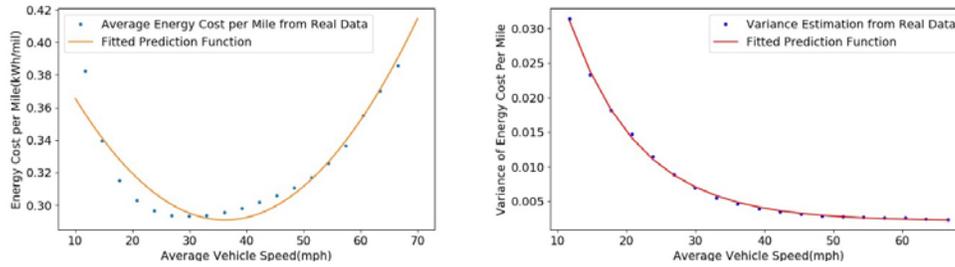


Figure II.9-2 - Left: Prediction function for average energy cost per mile; Right: Prediction function for variance of average energy cost per mile with regard to average vehicle speed

Two prediction functions derived from the real world data are listed as follows:

Mean prediction function of energy cost with regard to vehicle speed

$$F_{mp}(v) = 0.00011v^2 - 0.00786v + 0.43340$$

Variance prediction function of energy cost with regard to vehicle speed

$$F_{vp}(v) = 0.09073e^{0.09736v} + 0.00219$$

Case Studies for Optimal Charging Decision Making

A daily itinerary is selected from "Chicago Regional Household Travel Inventory (CRHTI)" in Figure II.9-3. The selected itinerary is a related long distance itinerary of about 172 miles during a weekday in Figure II.9-3. This itinerary comes from a financial planner. The optimal charging strategy is also provided in Figure II.9-3, including the charging station selection and amount of charged energy.

The whole itinerary dataset in CRHTI is used for case studies in Figure II.9-4. Results includes two simulation scenarios, including the charging necessity distribution with regard to initial EV energy state and the distribution of achievable itineraries under different optimal charging strategies, i.e., One-step and two-step prediction method (details can be referred in the publication [1]). Results show that the autonomous EVs equipped with the proposed automatic charging decision system can reduce the range anxiety.

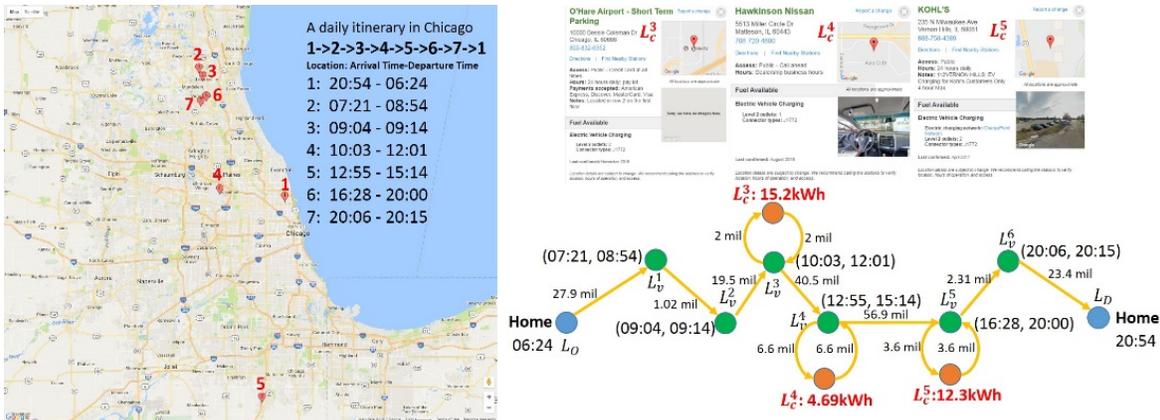


Figure II.9-3 - Left: An itinerary in CRHTI; Right: Optimal charging strategy for personal CAEV with a full battery capacity of 24kWh, including the charging station selection and the amount of charged energy

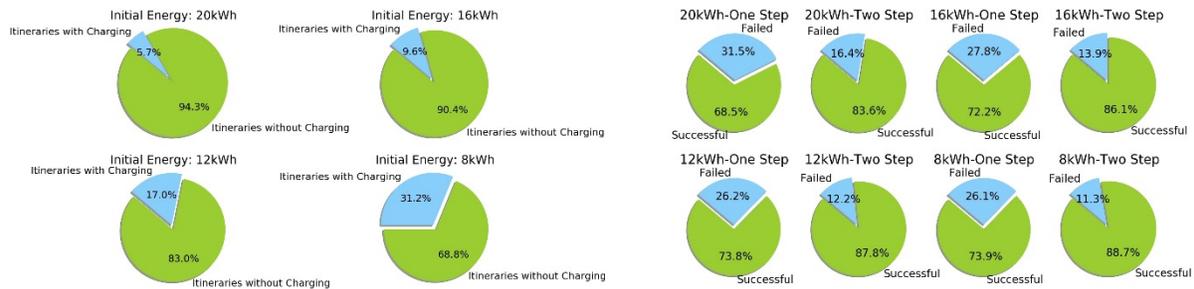


Figure II.9-4 - Left: Distribution of charging necessity; Right: Distribution of achievable itineraries under different optimal charging strategies.

Energy Impact Evaluation for Eco-Routing and Optimal Charging Decision Making of CAEV Fleet

A simulated transportation network in New York City in Figure II.9-5 is constructed for case studies. In total, 15 centroids are obtained from taxi pick-up locations by using K-means clustering method. There are two DC fast charging stations in Manhattan. The detailed available road segments are shown in Figure II.9-5. Each CAEV in this fleet assumes to be equipped with a designed eco-routing and charging decision making algorithm, which can be referred in the publication [2]. In the case studies, a fleet of 100 CAEVs has been utilized and each of them performs 100 trips that are generated according the pick-up and drop-off information in a New York EV Taxi dataset. Based on this fleet travel demand, energy impact has been analyzed under different ambient temperature that are shown in Table II.9-1.

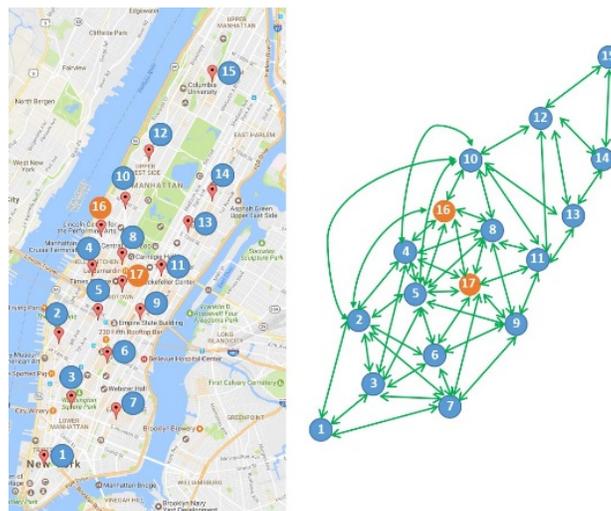


Figure II.9-5 - Transportation network for energy impact evaluation of CAEV fleet (Node 1 - Node 15 are road nodes and Node 16 and 17 are DC charging station locations)

Table II.9-1 - Temperature in New York City

Month	Temperature(°C) (Low, High)	Month	Temperature(°C) (Low, High)
January	(-3.1, 3.8)	February	(-1.9, 5.5)
March	(1.9, 9.9)	April	(6.9, 15.7)
May	(12.6, 21.5)	June	(17.7, 26.3)
July	(21, 29.3)	August	(20.3, 28.4)

Figure II.9-6 illustrates the overall energy consumption under the average lower and high temperature within each month. The corresponding average overall energy consumption in different months is provided too. It is obvious to notice that EV fleet has much smaller energy consumption in April and October. We can also see that EVs in months with very low temperature consume more energy by the same fleet and travel demand. This means that the cold weather has bigger effect on the energy consumption of autonomous EV fleet.

Figure II.9-7 illustrates the charging demand in charging stations of Node 16 and 17, respectively. The average charging demand in each month is calculated at average low and high temperature. For charging station Node 16, it has smaller charging demand in April and September; for charging station Node 17, it has smaller charging demand in May and October. Both charging stations demonstrate the heterogeneous charging demand pattern. Generally charging station Node 17 receives more charging demand than charging station Node 16 during these studies. The same features, e.g., charging power and enough charging points for every request, are assumed. Then these difference of charging demand are caused by specific locations of charging stations in the investigated transportation network and also the realistic travel pattern of autonomous EV fleet.

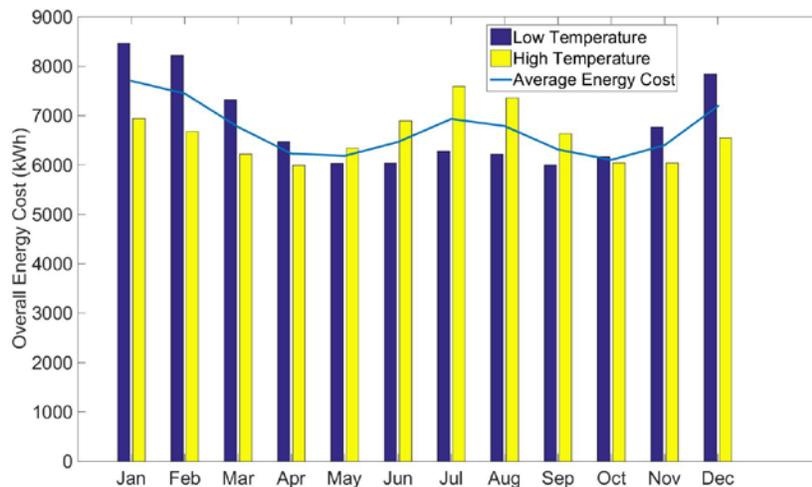


Figure II.9-6 - Overall energy cost of a CAEV fleet during different months for a given transportation demand

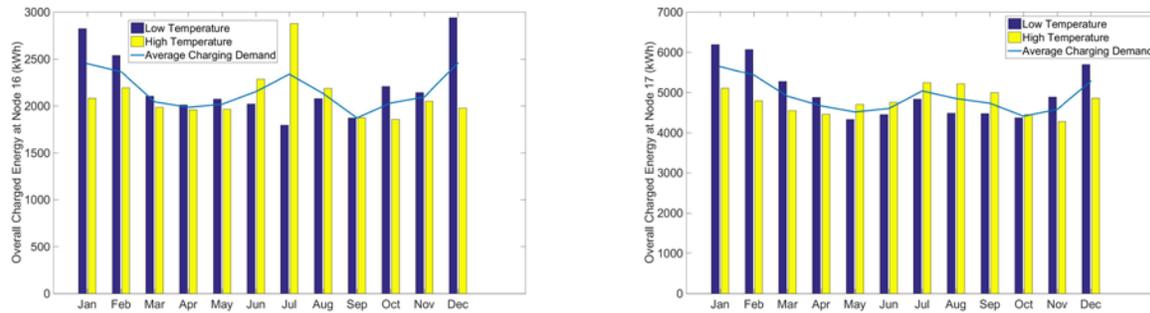


Figure II.9-7 - Charging demand of a CAEV fleet in different months for a given transportation demand: Left: Charging Station Node 16; Right: Charging Station Node 17

Conclusions

Optimal charging decision-making has been studied for personal CAEVs. A data-driven method based on EV project data in INL has constructed a multi-channel stochastic energy consumption prediction framework. Charging decision-making models are established for optimal charging strategies during a daily itinerary in order to minimize the charging cost outside home. Case studies by using real world itinerary data demonstrate the functionality of the introduced methodology. Results show the potential ability of personal CAEVs to reduce the range anxiety and charging infrastructure dependency. This means the autonomous vehicle technology is helpful to accelerate the electrification of personal vehicles.

Energy impact and charging demand have been evaluated under different ambient temperature for autonomous electric vehicle fleet. Data-driven models are studied based on a New York Nissan Leaf Taxi dataset. A data-driven grid stochastic energy consumption model with regard to average speed and ambient temperature is designed to emulate heterogeneous energy consumption behaviors of vehicles in an autonomous EV fleet. The introduced eco-routing and charging decision making framework has potential to be applied in autonomous EV fleet to improve the transportation efficiency and simulate driving activities for autonomous fleet. Case studies show the large impact of ambient temperature on energy consumption and charging demand for CAEV fleet. These illustrate challenges to optimally balance the energy supply from grid and dynamic energy need from autonomous EV fleet under different realistic conditions. These studies provide the potential capability to understand these challenges and aid in designing promising sustainable control strategies in future fleet management.

All models and algorithms developed in this project can be applied in the agent-based transportation simulation platform to describe the energy cost, driving and charging behavior of CAEVs. These models and algorithms are the fundamental work to provide high fidelity results for system-level transportation simulation with CAEVs.

Key Publications

1. Zonggen Yi, Matthew Shirk. "Data-Driven Optimal Charging Decision Making for Connected and Automated Electric Vehicles: A Personal Usage Scenario". Accepted in Transportation Research Part C: Emerging Technologies. (in publishing)
10. Zonggen Yi, John Smart, Matthew Shirk. "Energy Impact Evaluation for Eco-Routing and Charging of Autonomous Electric Vehicle Fleet: Ambient Temperature Consideration". Submitted to Transportation Research Part C: Emerging Technologies.

II.10 Generalized analytical methodology and computational tool development to support CAV energy impact assessment on a transportation system [Task 7A.2.3]

Jackeline Rios-Torres, Principal Investigator

Oak Ridge National Laboratory
2360 Cherahala Boulevard
Knoxville, TN 37921
Phone: (865) 946-1542
E-mail: riostorresj@ornl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$115,000

End Date: September 30, 2017
DOE share: \$115,000

Non-DOE share: \$0

Project Introduction

This task will seek to develop an analytical and computational platform that could be used to evaluate the system level impacts of vehicle connectivity and automation on energy usage, and travel time while also providing insights regarding ways to improve a given system using CAVs technologies and transportation system optimization. For a given transportation system, the tool will allow for multi-objective analysis and optimization of different CAV functionalities at varying penetrations incorporating issues such as shared mobility and congestion. Using analysis from this tool, the cities could develop policies or make projections regarding the impact of CAVs technologies on their transportation system.

Objectives

To develop an analytical and computational framework that will allow for multi-objective analysis and optimization of different CAV-based functionalities and/or services at varying penetrations incorporating issues such as shared mobility and congestion.

Approach

Partner: Boston University

- Selecting a transportation mode for simulation and optimization that will allow the exploration of the requirements and limitations involved in the development of the analytical and computational platform (we chose a shared Autonomous Taxi (AT) mobility system).
- Exploring available data sources for different transportation modes that can be used for the development of the platform.
- Using stochastic control approaches to develop models and optimization frameworks for efficient operation of transportation modes based on CAVs
- Expanding the capability of the platform to simulate additional transportation modes

Description of the shared Autonomous Taxi (AT) mobility system

The AT system consists of a set of neighborhoods which locally manage a queue of idle vehicles to respond to demand (ride requests originating at the neighborhood). We are specially focusing on the load balancing aspect in such systems, i.e., how to dynamically dispatch idle vehicles from one neighborhood to another to a) ensure

that demand across all neighborhoods is met, and b) minimize the empty vehicle traffic which contributes to congestion and additional energy consumption.

We are developing a queueing model for this dynamic system which reduces to a controlled Markov Chain. Demand rates are parameters in this model which may be found from real aggregated taxi data. The state space is comprised of the number of idle available taxis in each neighborhood, the number of taxis serving passengers, and the number of empty taxis in route between neighborhoods. The decision (control) variables are whether to dispatch an empty (no passengers) taxi and, if so, to which neighborhood.

The dynamics of this system are event-driven, i.e., the system state only changes at times when an event occurs. Events are either uncontrollable or controllable. Uncontrollable events are user requests for service, taxis dropping a passenger and becoming available for a new ride, and empty taxis arriving at a neighborhood. Controllable events occur when an empty taxi is dispatched from one neighborhood to another.

The objective is to minimize a weighted sum (convex combination) of the fraction of ATs driving empty ($f_1(u_{i,j})$), and the fraction of potential passengers rejected by the system $f_2(u_{i,j})$, due to the lack of available idle ATs at their pickup neighborhood (equation 1).

$$J = \min\{W_1 f_1(u_{i,j}) + W_2 f_2(u_{i,j})\} \quad (1)$$

Where W_1, W_2 are the penalty weights and, $u_{i,j}$ is the control input. This objective captures the trade-off between energy efficiency and quality of service. The optimal control policy, i.e., the decision to either send one idle AT from some neighborhood i to some other neighborhood j , or not send any empty ATs, is a function of the current state. Notably, the state space and control possibilities grow combinatorially with the number of neighborhoods and ATs in the system.

Determining an optimal load balancing policy is possible through standard Dynamic Programming (DP) methods, but the curse of dimensionality limits these methods to systems with just a few neighborhoods and ATs. For larger, more realistic, systems these methods are computationally prohibitive and require approximation methods for solving DP equations or alternative approaches that optimize selected classes of policies with desirable properties.

Results

To test the proposed baseline control and have some insights into the effectiveness of the proposed controller, we simulated a system consisting of two neighborhoods for 100 trials of 24 h each, assuming random traveling time and the following average demand rates:

- Passengers wanting to travel inside neighborhood 1: 10 passengers/hour
- Passengers wanting to travel from neighborhood 1 to neighborhood 2: 0.01 passengers/hour
- Passengers wanting to travel from neighborhood 2 to neighborhood 1: 0.01 passengers/hour
- Passengers wanting to travel inside neighborhood 2: 5 passengers/hour

Table II.10-1 - System simulation results

Scenario	Average % of users rejected	Average % of time AT drives empty
No control	40.99	0
Optimal control	28.99	0.08

The results in Table II.10-1, makes evident the trade-off between the objectives of the cost function, i.e., to improve the quality of service and reduce the number of users unable to get an autonomous taxi more ATs will need to travel empty between the neighborhoods.

Conclusions

We have developed an optimization framework for dynamic resource allocation in urban mobility systems based on the use of dynamic programming. This framework will allow us to test the performance of alternative less computationally intensive methods that will be developed. Given the computational limitations, we are currently exploring what is the largest mobility system size that can be simulated using the high-performance computing resources from Boston University. This will establish a baseline for comparing alternative methods to these results, as well as provide insights to the key features that characterize an optimal policy. Next, we will identify a class of policies characterized by a set of controllable parameters which we can later optimize in a data-driven adaptive manner using perturbation analysis techniques which could be less computationally intensive.

Based on our partner’s (Boston University) experience with a multitude of resource contention systems and load balancing problems arising in other domains, these parameters are normally thresholds on the states of the system that impose a partition on the state space. Therefore, the policies we derive are functions of a properly selected region of the state space rather than each point in this space. We can compare simulation results of our parametric control policy to the optimal control found by dynamic programming in order to assess the competitiveness of our parametrized methods. We can also tune a parametric control policy to a large system with demand rates conglomerated from publicly available taxi data set of an urban area.

Note that to expand our analytical and computational platform to include additional transportation modes in an urban area, the computational burden will increase. In this case, the high-performance computing resources at ORNL could be utilized.

Key Publications

1. Swaszek, R., Cassandras, C., and Rios-Torres, J. “Dynamic Resource Allocation for Energy-Efficient Urban Mobility” (Preliminary report in progress)

II.11 Truck CACC/Platooning Testing: Measuring Energy Savings, Interaction with Aerodynamics Changes and Impacts of Control Enhancements [Task 7A.3.1]

Steven E. Shladover, Sc.D., Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road
Berkeley, CA 94720
Phone: (510) 665-3514
E-mail: SEShladover@lbl.gov

Xiao-Yun Lu, Ph.D., Co-Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road
Berkeley, CA 94720
Phone: (510) 665-3644
E-mail: XiaoYunLu@lbl.gov

Michael Lammert, Co-Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-4067
E-mail: Michael.Lammert@nrel.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2019

Total Project Cost: \$1,009,000

DOE share: \$ 1,009,000

Non-DOE share: \$0

Project Introduction

This project was established to produce solid experimental data to provide authoritative estimates of the energy savings that could be achieved through cooperative automation of heavy trucks using cooperative adaptive cruise control (CACC) or more tightly coupled platooning technology. A variety of prior projects in the U.S. and overseas have estimated these energy savings, with results that have been difficult to compare and reconcile with each other because of differences in operating conditions or experimental procedures. This project will apply consistent approaches across a wide range of conditions to produce results that can be presented to industry stakeholders to provide them with the knowledge they need to make well-supported decisions about investing in the technology for their trucks.

Objectives

The objectives of this project include:

- (a) Refining the performance of the truck CACC system that was previously developed by the Berkeley team to emphasize energy efficiency in its vehicle following control logic
- (b) Enhancing the ability of the truck CACC system to detect and respond to cut-in vehicles so that it can make smoother and more energy efficient transitions between its different vehicle following modes of operation

- (c) Applying the SAE J1321 fuel economy test protocols to measure the fuel consumption of all of the trucks in a three-truck platoon or CACC string under a wide range of operating conditions
- (d) Applying the same SAE protocols to compare the fuel consumption of the three-truck configuration with a two-truck configuration, a long combination vehicle (LCV) and single trucks under various conditions
- (e) Developing a better understanding of the effects of changes in truck separation on the air flow around the trucks and through the radiator, and on the temperature of the trucks' engine compartments
- (f) Extending the cooperative vehicle following capabilities of the trucks from freeway operations to signalized arterial operations, using traffic signal phase and timing (SPaT) information to adjust speed profiles to enhance energy efficiency
- (g) Measuring the energy efficiency improvements that could be gained from use of the SPaT information under controlled test conditions
- (h) Measuring the energy efficiency improvements that could be gained from cooperative vehicle following control in real-world truck fleet operations.

Approach

This project is capitalizing on the prior development of the basic heavy truck CACC and platooning capabilities by the Berkeley team under the sponsorship of the FHWA Exploratory Advanced Research Program. Starting from three Volvo Class-8 truck tractors that have already been equipped with the needed sensors, communication devices, data bus interfaces and control system, this project has enhanced the control software and logic to produce smoother responses to grades and traffic disturbances and has been working on improving the ability of the system to detect cut-in maneuvers by drivers of other vehicles. This work is continuing with further efforts to work around constraints imposed by lower-level software embedded in the Volvo production vehicle platform. These enhancements are tested continuously through the development process by driving the trucks on public freeways near Berkeley, under special authority granted by the State of California.

The trucks were transported to Blainville, Quebec, Canada for an extensive series of tests at Transport Canada's Motor Vehicle Test Centre, where they were driven around the four-mile oval track under a wide range of operating conditions, following the widely accepted SAE J1321 fuel economy testing protocol. The trucks were instrumented with auxiliary fuel tanks that were weighed carefully before and after each test run to measure the change in fuel mass, as well as air flow measurement instruments on the hood and in front of the radiator, torque sensors on the drive shafts and temperature sensors under the hoods. Using these combinations of measurements, the aerodynamic effects can be separated from the other effects that influence fuel consumption, and potential problems associated with engine cooling that have been identified in prior tests can be investigated in more depth. These tests were conducted with close cooperation from the National Research Council of Canada and Transport Canada (which provided extensive financial support for the testing work).

The data from the Blainville testing are still being analyzed, and some preliminary results from the initial analyses of the data are summarized below in the Results section. The trucks have returned to California, where further refinements to their cooperative control systems are being developed and evaluated and the experiments associated with the arterial traffic signal system interactions planned for the second year of work will be conducted at the University of California's Richmond Field Station.

Results

The performance of the truck CACC control system that was originally developed under FHWA sponsorship was enhanced to produce smoother vehicle responses to disturbances, which is good for ride quality, traffic flow dynamics and energy consumption and emissions. Its ability to detect and respond to cut-in vehicles was also enhanced. These enhanced capabilities were the starting point for the extensive series of fuel economy tests that were performed in cooperation with Transport Canada. These tests have produced a very rich set of data to characterize the energy consumption of the trucks under a wide range of conditions, as well as detailed measurements of the air flow around the front of the trucks and through their radiators and of the temperatures

in their engine compartments. At this point, the analysis has been done on the energy consumption data, with additional analyses still to be performed on the air flow and temperature data.

The energy consumption test results are probably the most comprehensive such results to be produced in any truck platoon test program to date. They provide confirmation of some of the phenomena observed in previous tests and produce new knowledge as well. The primary trends with regard to energy consumption as a function of the size of the gaps between the trucks are illustrated in **Error! Reference source not found.** and Figure II.11-2 below, for each individual truck and for the three-truck platoon as a whole. These results are displayed as a comparison of the energy consumption when driven in close formation compared to the same trucks

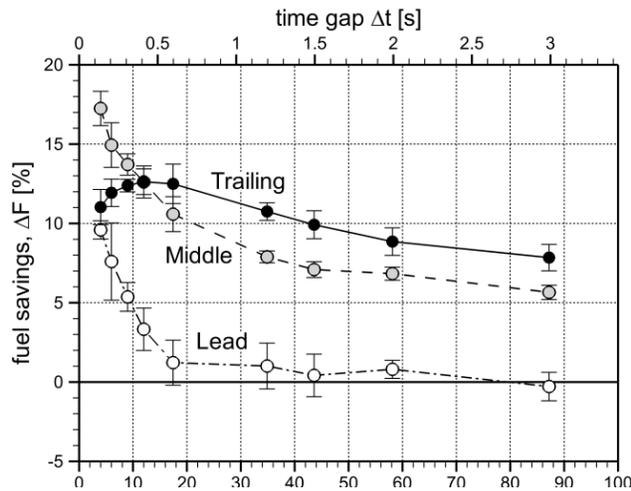


Figure II.11-1 - Fuel Savings for Individual Trucks as a Function of Separation Distance

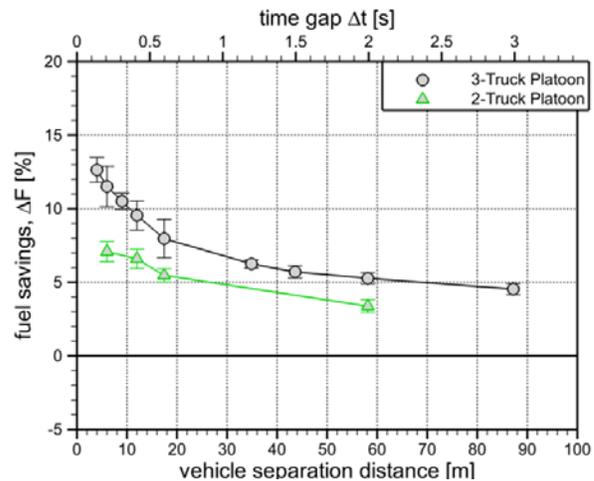


Figure II.11-2 - Average Fuel Savings for Two- and Three-Truck Platoons

Figure II.11-1 shows the fuel savings for each of the three trucks in the CACC platoon as a function of the separation distance (bottom scale) or time gap (top scale) at a speed of 105 km/h. Note that the lead truck only saves significant energy at gaps of 18 m or less, but the middle and trailing trucks are saving 6% and 8% respectively even as far apart as 87 m. At gaps below 18 m the relationships become more complicated, with the lead truck's savings rising rapidly toward 10% as the gap decreases to 4 m, and the middle truck's savings rising rapidly toward 17% at the 4 m gap. In contrast, the trailing truck's energy saving peaks at about 13% in the 15 m range and then declines to 11% as the gap reduces toward 4 m. These trends are the consequence of different phenomena affecting the aerodynamics at the front and rear of each truck. Figure II.11-2 shows the average savings across the entire three-truck platoon, trending from about 5% at the 87 m gap up to 13% at the 4 m gap. It also shows a similar trend for a two-truck platoon, but with noticeably lower savings, ranging from about 2% less at a 58 m gap to 5% less at a 6 m gap. This indicates the incremental energy saving advantage of extending the platoon length from two trucks to three. The energy saving of the two-truck platoons was also compared to the energy saving when the same two trailers were operated in a long combination vehicle (LCV) configuration, pulled by a single truck tractor. The LCV saved 23% compared to two single isolated trucks, three times as much as the saving of the two-truck platoon.

Multiple experiments were done to explore the interactions of the platooned trucks with other traffic sharing the same test track. When one of the trucks followed an SUV at gaps between 43 m and 87 m, it saved between 1.5% and 2.5% of the fuel that it consumed when driving in isolation, indicating that trucks are probably already achieving some fuel savings in their normal operations. One of the major concerns that has been expressed about operations of trucks in platoons is the cut-ins that they experience from drivers of other

vehicles. The effects of very frequent cut-ins were tested by staging cut-in maneuvers every 2 miles during the tests, once on each of the straight sections of the test track, lasting for 30 seconds before the intruder vehicle cut out. The energy penalties associated with these periods of driving at longer than normal separations and with the extra speed changes needed to respond to the cut-ins were encouragingly small. When the cut-in was between the first and second truck, the second truck gave up only 1% of its fuel economy improvement, and when it was between the second and third trucks, the third truck lost between 1.5% and 2.3% of its fuel economy improvement.

The fuel consumption measurements from the laborious and time-consuming SAE J1321 fuel weighing procedures were compared against simultaneous measurements of fuel injector data from the trucks' data buses, and these comparisons were used to calibrate the data bus measurements so that they could be used for finer-grain assessments of variations within the test runs (not just the total fuel consumption for a complete sequence of 16 laps of the test track). The comparisons of these results are illustrated in Figure II.11-3, which shows that the comparisons tracked very closely except for the trailing truck at the shortest gap settings.

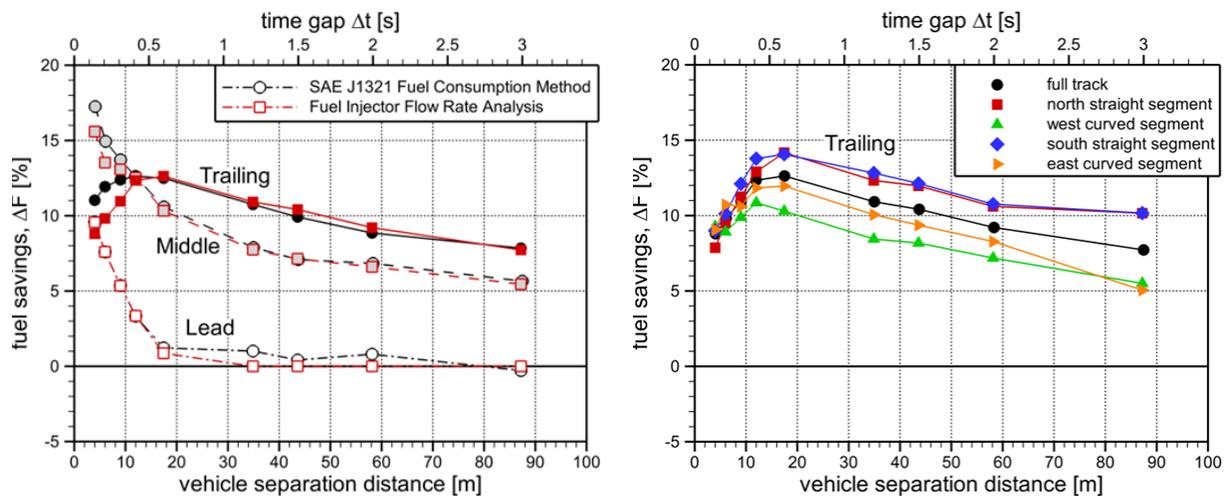


Figure II.11-3 –(Left) Comparison of J1321 Fuel Weighing and CAN bus showing Fuel Injector Signal Measurements of Fuel Consumption and (Right) CAN bus Fuel Injector Measurements Delta Fuels Savings on Straight and Curved Track

Figure II.11-3 shows how the CAN bus measurements from the fuel injectors can be used to compare the fuel economy savings on the straight and curved sections of the test track. These indicate that the savings on the straight sections of the track are about 2% larger than the average savings measured along the entire track. This means that trucks that are driven on essentially straight roads may be expected to save up to 2% more energy by driving using CACC or platooning systems than shown in the results for the complete test runs as shown in **Error! Reference source not found.**

Conclusions

- The three-truck data demonstrated a wide range of fuel savings, with the lead vehicle experiencing up to 10% at the closest separation distance of 4 m, with the middle vehicle also experiencing a maximum fuel saving at the shortest distance of 17%, and with the trailing vehicle experiencing a maximum fuel savings of 12% within the range of 10-20 m.
- Significant fuel savings for the middle and trailing vehicles were measured at the largest separation distance of 87 m, with 6% and 8%, respectively, indicating a significant likelihood that trucks are already receiving some benefits from drafting in normal traffic.
- Total fuel savings for the three-vehicle CACC string was measured at 13% at the shortest separation distance of 4 m, with 4.5% savings measured at 87 m.

- The lead and trailing vehicles of the two-truck CACC demonstrated the same trends in fuel savings with separation distance as the three-truck CACC, but with a lower magnitude for the trailing vehicle.
- Trends in data compare well with other fuel-economy data sets for similar vehicle types, speeds, and weights. Three-truck data also match trends observed in a wind-tunnel test.
- A reduction in fuel savings in excess of 1% was observed at small separation distance (12 m) when mismatched trailers were introduced into the CACC configurations, although the differences were generally within the confidence intervals of the data. No change in fuel savings was observed at 58 m separation distance.
- For equivalent cargo weights, a two-trailer long combination vehicle (LCV) provided a greater fuel savings than the best performing two-truck CACC scenario (23% for LCV compared to 7% for CACC).
- A reduction in fuel savings from the CACC on the order of 1-2% was measured when a periodic speed variation between 89 and 105 km/h was introduced every 100 seconds, with the CACC set to a 1.2 seconds time gap.
- Other road traffic can influence the fuel savings of cooperative heavy-vehicle automation systems. Some data shows beneficial effects of a platoon following an SUV, while other data showed no such benefit. Periodic cut-ins between the trucks showed no appreciable change in the fuel savings of the three-truck CACC with a separation time gap of 1.2 s (target distance of 25 m).
- Two approaches to evaluating differences in fuel savings between the straight and curved segments of the track revealed reduced fuel savings on the curved roadway.

Key Publications

1. Muratori, M., Holden, J., Lammert, M., Duran, A., Young, S. and Gonder, J., 2017. Potentials for Platooning in US Highway Freight Transport. *SAE International Journal of Commercial Vehicles*, 10(2017-01-0086), pp.45-49.
2. X.-Y. Lu and S.E. Shladover, "Integrated ACC and CACC Development for Heavy-Duty Truck Partial Automation", American Control Conference, Seattle, WA, June 2017.

II.12 Collection and Analysis of CAVs-Relevant Real-World Vehicle Data [Task 7A.3.3]

Jeff Gonder, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-4462
E-mail: Jeff.Gonder@nrel.gov

Matt Shirk, Principal Investigator

Idaho National Laboratory
2525 Fremont Ave
Idaho Falls, ID 83402
Phone: (208) 526-7216
E-mail: Matthew.Shirk@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2017

Total Project Cost: \$687,000

DOE share: \$687,000

Non-DOE share: \$0

Project Introduction

Connected and automated vehicles (CAVs) offer the potential to enhance driver safety, comfort, and mobility as well as fuel efficiency. As interest in CAVs technologies has grown, automakers have announced plans to introduce vehicles utilizing them into the market. However, real-world evaluation of the operational and energy consumption differences between CAVs and comparable manually-driven vehicles remains quite limited. To help fill this information gap, this project seeks to work with partners to collect and analyze data on energy impacts from early vehicle automation deployments and to validate modeling estimates of connectivity-enabled fuel saving features such as green routing. Due to space limitations, this report will only focus on collaboration work with Volvo Car Corp. (VCC), which plans to launch a large-scale pilot deployment of automated vehicles in Gothenburg, Sweden, known as the "Drive Me" project [1].

In preparation for the Drive Me project, VCC and NREL collaborated to analyze operation of partially-automated vehicles over the Drive Me route in Gothenburg. These vehicles were equipped with adaptive cruise control (ACC), which used a radar sensor to detect the distance to the nearest leading vehicle, as well as the speed of that vehicle, and adjusted the ACC-equipped vehicle's speed to maintain a preferred gap (1–3 seconds) between the vehicles. Similar to a traditional cruise control request, drivers could activate ACC manually, and deactivate ACC by braking or override it by pressing the accelerator pedal [1].

This ACC field test presents an opportunity to address multiple data gaps related to partially automated vehicle operation. It enables analysis of ACC vehicle operation and fuel consumption impacts compared with fully manual driving under different traffic and road conditions—areas lacking in past research. Through the course of the NREL/VCC collaboration, VCC published its initial analysis of the ACC operational impacts [1], and the work summarized in this report provides an independent comparison to that initial analysis, as well as an expansion where the fuel consumption impacts under different driving conditions are weighted to obtain an aggregate impact estimate at the road network level. In addition, NREL's analytical framework for the ACC study can be replicated for analyzing the operational and energy impact differences between the higher level of vehicle automation that will be evaluated in the Drive Me pilot relative to comparable manual driving.

Objectives

This project analyzes the real-world operational and fuel economy impacts of partial vehicle automation, specifically the use of ACC. Objectives include the following:

- Examine vehicle operation and fuel use differences between ACC and non-ACC driving on the test route to be used for VCC's Drive Me project
- Develop and apply an objective methodology for calculating the aggregate fuel efficiency impacts of ACC vs. non-ACC mode, producing results weighted by the total driving occurring under each driving condition (based on traffic speed and road grade)

Approach

Data were collected from VCC's field test of ACC-capable vehicles over the Drive Me route in Gothenburg. The three similar Volvo diesel automatic models were driven by VCC employees and family members on more than 160,000 trips. Data collected included vehicle and engine speed, vehicle fuel consumption, pedal positions, GPS position, ACC status, distance to the nearest leading vehicle and the speed of that vehicle, as well as ambient temperature and weather conditions.

The first step in the NREL analysis was to classify ACC and non-ACC trips based on whether vehicles had ACC on or off. Next, the trips were separated into segments of 0.5 km or smaller, and these segments were matched to road links on a base map provided by TomTom, Inc.⁵ The segment data were categorized by road grade and by the average traffic speed at the time of travel to enable comparison of the two vehicle modes under common operating conditions. Traffic speed was estimated using the average road link speed at time of travel from historic TomTom traffic data, when available. When these data were not available, the average traffic speed was represented by the average speed from the test vehicle's GPS trace. The data were used to statistically analyze the operation of vehicles in ACC and non-ACC mode by driving condition.

Next, the fuel consumption rates (FCRs) for the vehicles in ACC and non-ACC modes were analyzed. These calculations were based on parameters reported from the test vehicles' data bus, which VCC reported to be accurate. The final FCR calculations also included an adjustment for the difference in a vehicle's speed at the beginning of a sample segment vs. the end of the segment (accounting for the fact that net deceleration over a segment decreases the FCR, whereas net acceleration increases the FCR).

The differences in FCR between ACC and non-ACC modes were used to create FCR ratios:

$$FCR\ ratio = \frac{ACC\ FCR}{non - ACC\ FCR}$$

At any given driving condition, an FCR ratio below 1 means the ACC mode's FCR was lower than the non-ACC mode's, and a ratio above 1 means the non-ACC mode's FCR was lower than the ACC mode's. The FCR ratio data were classified by traffic speed and road grade, and the resulting values were assessed for statistical significance, yielding a matrix of significant FCR ratio values across various speed-grade bins.

The final step was to use the results from the test vehicles to estimate the aggregate fuel consumption differences at the Drive Me road network level for vehicles traveling in ACC vs. non-ACC mode, based on appropriately weighting the total amount of travel that occurs on the network under different driving conditions. This required first estimating the total vehicle kilometers traveled (VKT) under each driving condition experienced by all vehicles traveling on the network. Ground-truth traffic-flow (vehicles per hour)

⁵ Each of these segments became a unit of analysis for the operational behavior under different driving conditions; for example, an ACC sample size of $n = 16,774$ means that the sample includes 16,774 segments that were driven in ACC mode.

data were matched spatially to TomTom road links, and the flow and link attribute data were used to train a neural network traffic flow estimation model. The model performed reasonably well, with an accuracy rate (1 – RMSE %) of 68% and R^2 of 0.85 (Figure II.12-1).

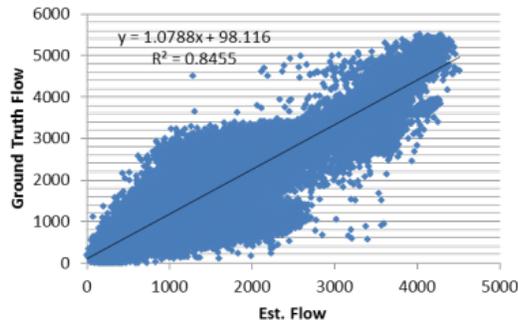


Figure II.12-1 - Correlation of ground-truth data (from multiple fixed traffic detector locations) with model-estimated traffic flow

The model was applied to all test route links over a full year to calculate overall VKT. The VKT were disaggregated by average traffic speed and road grade, resulting in a VKT matrix that corresponds with the FCR ratio matrix described above. A weighted average FCR ratio was then calculated by weighting each binned FCR ratio value by the relative amount of travel indicated in the corresponding VKT bin.

Results

Characterizing ACC and Non-ACC Vehicle Operation and Fuel Use

The sample of ACC driving data contained significantly fewer low-speed driving segments than in the non-ACC data. According to VCC, ACC can only be activated when the vehicle is above 30kph, which no doubt contributes to this difference. However, the ACC driving data did include some segments with driving speeds below 30 kmph, so presumably ACC can remain active at these speeds if it is turned on at a higher speed before traffic conditions force the vehicle to slow.

Focusing on driving segments in traffic conditions ranging from 40–110 kmph (where the vast majority of the ACC and non-ACC sample data occurs) Figure II.12-2 compares acceleration standard deviation distributions for each driving mode. Higher acceleration standard deviation indicates more rapid changes in vehicle acceleration and would be expected to correlate with higher fuel consumption rate (relative to smoother driving with lower acceleration standard deviation). The figure shows comparable comparisons for the standard deviation of both acceleration and deceleration rates for ACC relative to non-ACC modes, with the results not surprisingly indicating overall smoother driving behavior from ACC operation (the average acceleration/deceleration standard deviation in ACC mode was +0.22/-0.21 m/s² compared with +0.29/-0.29 m/s² in non-ACC mode⁶). An initial comparison of the average (unweighted) fuel consumption rate for the ACC relative to the non-ACC samples confirms a lower FCR for ACC (roughly 5.4% lower than the average FCR in non-ACC mode⁷). However, accurately estimating a network-wide benefit of ACC compared to non-

⁶ The differences in average accel/decal standard deviation are significant at the 95% confidence level. Sample sizes were n = 8,482 (positive/acceleration) and n = 8,137 (negative/deceleration) for ACC and n = 26,105 (positive/acceleration) and n = 32,029 (negative/deceleration) for non-ACC.

⁷ The fuel consumption difference is significant at the 95% confidence level. Sample sizes were n = 16,774 for ACC and n = 60,932 for non-ACC.

ACC requires further effort to disaggregate the FCR differences by driving condition and then to calculate a weighted average of those differences by the amount of driving that occurs in each condition.

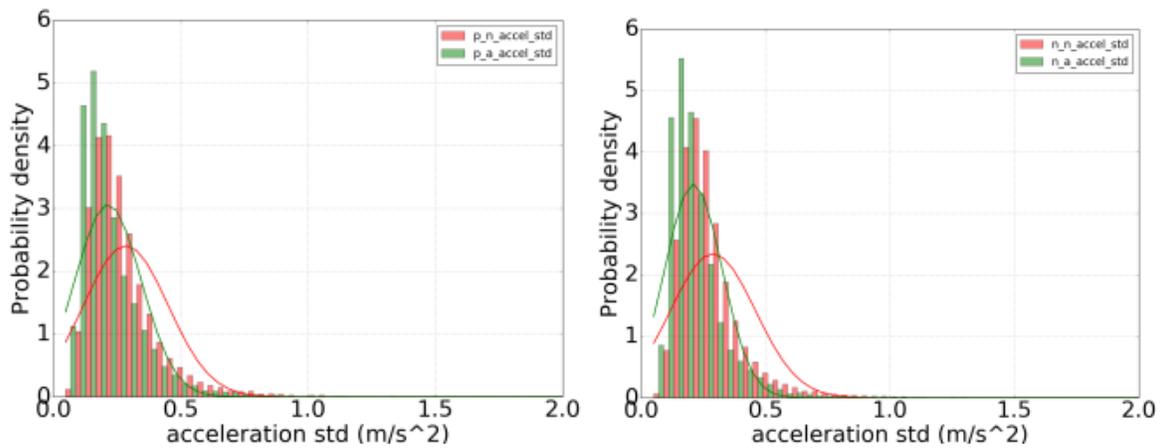


Figure II.12-2 - Distributions of acceleration (left) and deceleration (right) standard deviations in ACC and non-ACC modes

Weighting ACC Fuel Economy Improvement by Driving Condition and Vehicle Kilometers Traveled

Figure II.12-3 shows FCR by speed bin for ACC and non-ACC operation as well as the FCR ratio. As expected, FCRs are higher at lower speed bins and lowest in the 60–100 kmph range, where overall driving is smoother but not overly penalized by exponentially increasing aerodynamic drag at very high speeds. The difference between ACC and non-ACC FCRs is largest at lower speeds, and a small difference persists at speeds above 60 kmph. Figure II.12-4 shows the FCR results by grade % bins. Unsurprisingly, FCR increases as grade increases. The difference between ACC and non-ACC FCRs is largest at negative grades, narrows for relatively flat driving, and is smallest for uphill driving.

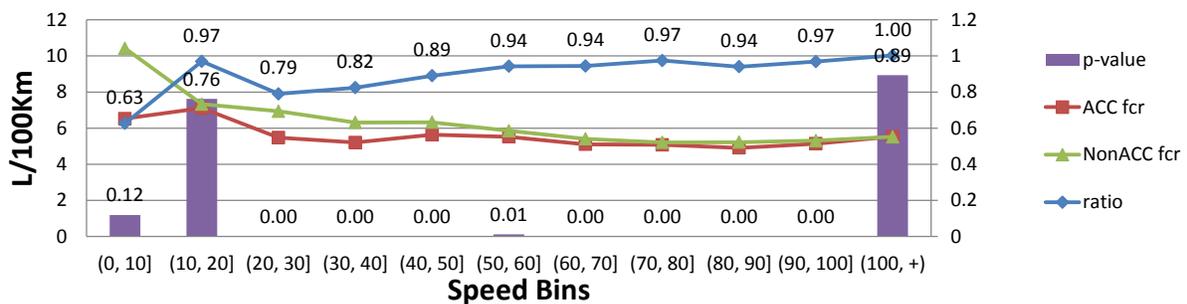


Figure II.12-3 - FCR and FCR ratio by speed bins⁸

⁸ In this figure and similar figures, parentheses represent exclusive values, and brackets represent inclusive. For example (10,20] indicates > 10 and ≤ 20.

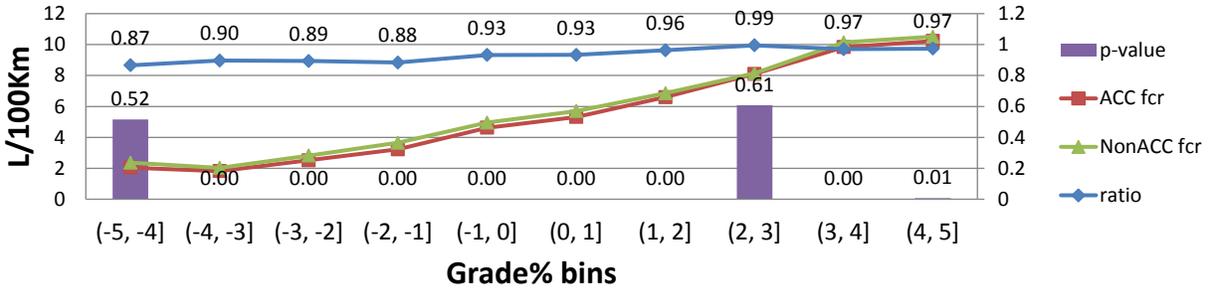


Figure II.12-4 - FCR and FCR ratio by grade % bins

Figure II.12-5 plots the FCR ratio results in two dimensions, with speed bins along the vertical axis and grade % bins along the horizontal axis. For example, at speeds of 70–80 kmph and grades of 0%–1%, the FCR ratio is 0.95. Light colors denote FCR ratios substantially lower than 1 (meaning ACC mode is substantially more fuel efficient), with the colors darkening for FCR ratios that approach and go beyond 1 (at values above 1, non-ACC mode is more fuel efficient). Cells only contain values if the data set contained the particular speed-grade combination and if the FCR ratio values are statistically significant at the 95% confidence level.

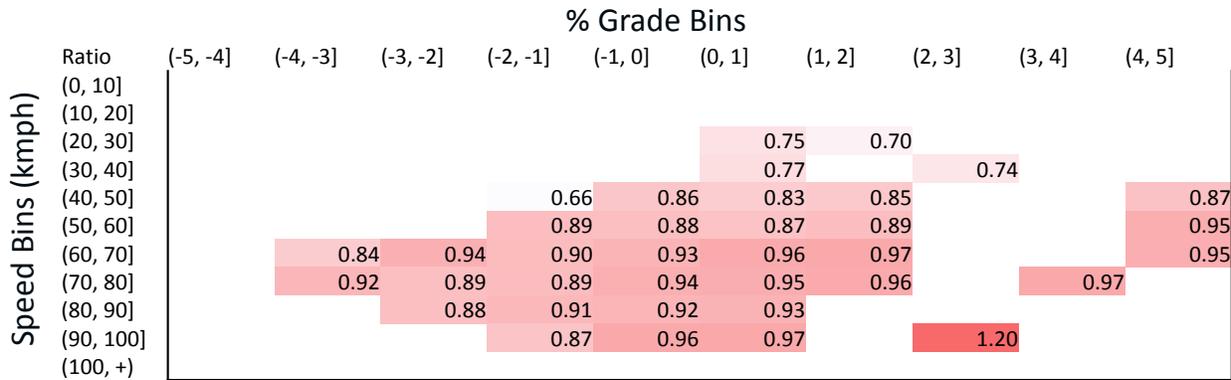


Figure II.12-5 - Variation in FCR ratio by speed and grade bin

The weighted FCR ratio calculation results from combining the FCR ratio matrix with the VKT matrix shown in Figure II.12-6. Using the Figure II.12-5 FCR ratio matrix in this calculation—that is, including only the populated cells in Figure II.12-5 and their corresponding cells in Figure II.12-6—results in the “as is” FCR ratio of 0.94 shown in Table II.12-1. In other words, the FCR of the ACC mode is estimated to be 6% lower than the FCR of the non-ACC mode based on the weighted average of all travel on the test route that occurs in the operating conditions where a statistically significant difference in the ACC relative to the non-ACC FCR was detected in the test data.

Table II.12-1 also shows an “educated guess” FCR ratio of 0.95. This value results from populating all the blank cells in Figure II.12-5 with values derived from polynomial regression equations.⁹ Under this assumption, the FCR of the ACC mode is estimated to be 5% lower than the FCR of the non-ACC mode based on the weighted average of all travel in the test route in all driving conditions (where extrapolated FCR ratio

⁹ The regression equations extrapolate the statistically significant values in Figure II.12-3 ($R^2 = 0.95$) and Figure II.12-4 ($R^2 = 0.86$).

estimates were used to populate driving conditions where the ACC and non-ACC test data in those conditions did not produce a statistically significant FCR ratio).

Finally, Table II.12-1 contains five FCR ratios from a sensitivity analysis, in which all the blank cells in Figure II.12-5 are filled with single constant values of 0.82, 0.88, 0.94, 1.0, or 1.06. Even under these disparate assumptions, the resulting FCR ratios vary only a small amount from the “as is” result—particularly for the reasonable approaches of extrapolating results from the statistically significant FCR ratio bins, and of assuming no difference (FCR ratio = 1.0) between ACC and non-ACC where statistically significant results could not be determined. It is reasonable to conclude that the operating conditions with uncertain FCR ratio have little impact on the network-level result (note from Figure II.12-6 that relatively little VKT occurs in those conditions, whereas the conditions with statistically significant FCR ratio values are those where most VKT occurs).

VKT (unit: million)		% Grade Bins									
		(-5, -4]	(-4, -3]	(-3, -2]	(-2, -1]	(-1, 0]	(0, 1]	(1, 2]	(2, 3]	(3, 4]	(4, 5]
Speed Bins (kmph)	(0, 10]	0.03	0.12	0.15	0.13	1.73	1.31	0.42	0.19	0.04	0.02
	(10, 20]	0.22	0.19	0.50	0.82	4.86	5.59	1.16	0.64	0.10	0.09
	(20, 30]	0.48	0.70	1.38	1.57	9.03	9.44	1.90	1.22	0.17	0.15
	(30, 40]	0.78	0.88	1.98	2.05	13.19	12.13	2.95	2.14	0.35	0.44
	(40, 50]	1.21	1.49	3.38	3.23	23.32	19.45	3.63	3.64	1.09	0.94
	(50, 60]	3.67	4.69	8.54	8.19	51.73	34.90	8.74	9.70	4.60	2.24
	(60, 70]	9.90	13.73	19.48	32.11	130.93	89.55	33.02	28.82	17.10	6.74
	(70, 80]	9.04	14.16	28.23	50.57	214.64	164.88	62.58	27.19	15.78	7.89
	(80, 90]	4.05	5.25	15.02	23.26	229.98	152.27	30.53	7.76	4.71	1.58
	(90, 100]	0.62	0.64	5.49	6.18	161.99	87.78	11.52	1.35	0.59	0.21
	(100, 110]	0.07	0.09	0.49	0.61	28.44	18.98	1.55	0.32	0.08	0.03

Figure II.12-6 - Variation in estimated VKT (millions) by speed and grade bin (high values in red/orange, low in green/yellow)

Table II.12-1 - Results—FCR Ratios Weighted by VKT, Including Sensitivity Analysis

Scenario	As Is	Educated Guess	Sensitivity (0.82)	Sensitivity (0.88)	Sensitivity (0.94)	Sensitivity (1.0)	Sensitivity (1.06)
Weighted FCR Ratio	0.94	0.95	0.92	0.93	0.94	0.95	0.96

Conclusions

The estimated VKT-weighted FCR for vehicles in ACC mode is about 5%–6% lower than for vehicles in non-ACC mode. Although having additional data would improve the coverage of FCR ratio bins with statistically significant values, the low VKT levels corresponding to the currently uncertain bins diminish the influence of these bins on the weighted result. In any case, the FCR result is comparable to the unweighted results comparison which showed 5.4% lower fuel consumption of ACC compared with non-ACC driving (suggesting that the driving sample was well representative of overall traffic conditions experienced on the network).

Further R&D options might include continuing to improve the traffic-flow estimation model and the VKT calculation approach. Contingent on availability of valid field test data, another options for further analysis may be the consideration of other powertrains, such as hybrid electric vehicles. Finally, the methods demonstrated in this study could be applied to analyze large-scale pilot deployment of higher-level vehicle automation under the Drive Me project in collaboration with VCC.

Key Publications

1. M. Pourabdollah, E. Bjarkvik, F. Fuerer, B. Lindenberg, and K. Burgdorf. “Fuel economy assessment of semi-autonomous vehicles using measured data.” Presented at the Transportation Electrification Conference and Expo (ITEC), 2017 IEEE, July 2017, Chicago, USA.
ieeexplore.ieee.org/document/7993365/citations
2. Zhu, L., Holden, J., Wood, E., and Gonder, J., “Green Routing Fuel Saving Opportunity Assessment: A Case Study Using Large-Scale Real-World Travel Data,” Proceedings of the 2017 IEEE Intelligent Vehicles Symposium (IV’17), June 2017, Redondo Beach, CA.

III. SMART Mobility – Mobility Decision Science (MDS)

III.1 WholeTraveler Study [Task 1.1]

C. Anna Spurlock, Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road, Mailstop 90R4000
Berkeley, CA 94720 USA
Phone: (510) 495-2072
E-mail: caspurlock@lbl.gov

Andrew Duvall, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-4783
E-mail: andrew.duvall@nrel.gov

Victor Walker, Principal Investigator

Idaho National Laboratory
PO. Box 1625
Idaho Falls, ID 83415
Phone: (208) 526-8959
E-mail: victor.walker@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2019

Total Project Cost: \$3,300,000

DOE share: \$3,300,000

Non-DOE share: \$0

Project Introduction

The WholeTraveler Study is designed to explore the energy implications of behavioral factors associated with adoption and use of emerging transportation technologies and services (connected and automated vehicles, mobility-on-demand, electric vehicles, e-commerce). The project uses an innovative, regionally-focused survey designed to understand the relationship between pivotal population characteristics, attitudes, and preferences, and their likelihood to adopt emerging technologies and services. In addition, the survey is designed to shape an understanding of how those technologies and services are likely to be used, how these uses are expected to affect the transportation system, and what the resultant energy implications may be.

Objectives

- Explore the question: how does the US traveler (segmented by demographics) make decisions impacting transportation energy use in the:
 - *Very short-term*: reroute, mode choice
 - *Short-term*: Day-ahead travel planning
 - *Medium-term*: Vehicle ownership & type

- *Long-term*: Housing location, etc.
- Identify historic patterns in lifecycle trajectories and map out relationships to transportation behaviors to be used to predict change-points and decision points when people would be most likely to respond to policy incentives.
- Couple definitions of heterogeneous traveler groups based on lifecycle trajectories with data on other dimensions of heterogeneity including personality/psychological traits, environmental preferences, metrics of risk aversion and intertemporal discounting, traditional demographic data, and other historic behavior patterns (such as technology adoption) to determine the most useful definition of heterogeneity that can best explain variation in behavioral outcomes of interest: openness to CAV and/or EV adoption/use, car ownership patterns, degree to which TNCs are compliments or substitutes to car ownership or public transportation use, and short-term, high-resolution travel behavior patterns (locational GPS data).
- Use insights from all of the above analyses to inform expansion and enrichment of agent-based modeling efforts within SMART Mobility.

Approach

The approach taken in this study involves a survey-based data collection, and subsequent analyses to answer a variety of research questions. The work for this study was performed by a team comprised of staff members from LBNL, NREL, and INL.

The survey will be conducted in two phases: (1) Phase 1 is an online survey collecting information on respondents: transportation needs and preferences, psychological characteristics of interest, demographic characteristics, and the timing of key historic life events; and (2) the second phase of the survey is a GPS data collection phase, where participants will provide a week's worth of their Google Location History GPS data collected on their smartphone, and answer a short series of questions about their transportation choices during that week.

The survey is focused in the 9 core counties of the San Francisco Bay Area (Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma). The sampling method used is an Address-Based random sample in this region. Invitation letters will be sent to 30,000 active residential mailing addresses in this study area, encouraging potential participants to go to a designated website to fill in the Phase 1 survey. The Phase 1 survey is administered online only, and is designed to take approximately 20 minutes on average to respond to. Upon completion of the Phase 1 survey, respondents are invited to participate in Phase 2. Those that opt in to Phase 2 will be provided with a series of simple instructions to select the necessary settings on their smartphones to enable Google to maintain their Location History. After a week, instructions will be provided for the respondents to download an archive of their Google Location History, and upload it to a web tool that will enable them to select the date range of the data they agree to submit, respond to a short series of questions, and transfer the data to a Lawrence Berkeley National Laboratory secure server. Respondents that complete Phase 1 will be provided with a \$10 Amazon gift card, and those that complete Phase 2 will be provided with an additional \$20 Amazon gift card. We anticipate an approximate 3% response rate for the Phase 1 survey, resulting in about 900 responses, and that 200 of these respondent will subsequently follow through and complete Phase 2 as well.

The survey design and subsequent analyses are geared towards answering a series of pressing questions:

1. What are, and what will be, the demand curves of travelers in a transforming transportation system? In particular, what are the barriers to and drivers of adoption and use of emerging technologies (connected and automated vehicles, mobility-on-demand, electric vehicles, e-commerce), how are they distributed across the population, and how do they compare to each-other in terms of degree of influence? Possible dimensions of heterogeneity relevant to understanding these barriers and drivers include: psychological

characteristics (Big Five: Openness, Conscientiousness, Extroversion, Agreeableness, Neuroticism); risk aversion; discount rate; lifecycle phases; commute needs/characteristics; intergenerational influencers; household composition; past technology adoption patterns; peer effects; preference for driving or driving ability/access; preferences over mode characteristics (travel time, cost, uncertainty of cost, uncertainty of travel time, ability to engage in other activities while traveling, ability to transport a child needing a car seat, ability to trip chain, hassle, safety, environmental preferences, level of interaction with others taking the same mode); and demographics.

11. What are the energy implications in the transportation system of these demand curves (barriers and drivers)?
 - 1.1. E-Commerce: to what extent is home delivery a compliment or substitute for trips to the store in several categories of purchases (prepared food, groceries, household items, clothing and accessories)? What are the biggest driving and dissuading characteristics of home delivery, and what implications does this have for scale up projections?
 - 1.2. Mobility on Demand / shared mobility: to what extent are Uber, Lyft or similar TNCs providing a service that compliments or replaces other transportation modes (including walking, biking, public transit, etc.), and at what cost points? To what extent does cost uncertainty (e.g., Uber surge pricing) influence peoples' willingness to depend on TNCs relative to other modes?
12. What are the underlying patterns and influencers of technology adoption? In particular, how does awareness of, exposure to, and interest in transportation technologies and services of interest, as well as proxy technologies, correlate with other relevant travel characteristics, needs, and preferences?
 - 1.3. Technologies: hybrid vehicles (gasoline-electric); plug-in electric vehicles; smartphones; rooftop PV; adaptive cruise control ("L1"); partially automated vehicles ("L2," e.g., Tesla "Autopilot"); fully automated vehicles ("L4"); Uber/Lyft or other TNCs (single passenger option); Uber Pool, Lyft Line or other TNC (carpool option); navigation or trip-planning apps (e.g., Google Maps, Apple Maps, WAZE); Amazon Prime account; and car-share services (Zipcar, Car2Go)
13. What are the dynamic lifecycle drivers and barriers to transportation decisions and their long-term energy implications?
 - 1.4. What are the primary archetypal lifecycle trajectory patterns across the population, and what are the correlations between key life phases and transportation choices (vehicle ownership and mode use) across these archetypal patterns?
 - 1.5. How do change points in lifecycle phases drive changes in transportation choices (vehicle ownership and mode use)?
 - 1.6. To what extent are these life phases, their change points, and their implications for shifts in transportation choices (vehicle ownership and mode use) predictable within an individual, or segments of the population?
14. Are the demand curves for these different emerging technologies and services interconnected? What is the degree of correlation between emerging technologies and services of interest in terms of propensity to adopt or use, or preferences for their defining characteristics?
15. What are the energy implications of the demand curves (barriers and drivers)? What is the degree of correlation between energy intensity of needs and preferences on the one hand, and propensity to adopt, use, or preferences over the emerging technologies and service of interest on the other?
16. What are the differences between stated preferences and actual travel patterns recorded in high-resolution day-to-day GPS observations? Are there indications of actual travel distance and methods that affect the priorities and preferences which travelers indicate? To what extent are travel choices (e.g., route and time

of departure) flexible within a given traveler and what implications would this have for energy consumption?

- Can these insights improve transportation system modeling and simulation flexibility, richness, and accuracy? Can a deeper understanding of heterogeneity across the population in terms of characteristics, preferences, propensity to adopt (demand curves for) these emerging technologies and services, as well as traditional mode use, fundamentally inform simulation models?

The analysis approach used will vary depending on the question being explored. For the most part, data analysis will use standard econometric and statistical techniques, such as linear regression and discrete choice modeling.

In some instances, the analyses approach itself will be innovative and novel. In particular, machine learning clustering methods designed for clustering multivariate sequences (such as Optimal Matching) will be used to identify archetypal lifecycle trajectory patterns. These clustered sequences, or archetypal patterns, can then be further analyzed to understand broad patterns in life phase transitions across the population, and the relationship between shifts in these patterns and critical transportation related decisions.

Results

We have completed almost all of the preparatory steps before the survey can be put into the field including: design, preparation, programming, and testing of the survey instrument and implementation methodology; approval of the Institutional Review Board (IRB) protocol by the Lawrence Berkeley National Laboratory Human Subjects Committee; and obtaining a comprehensive cyber security review of our data collection, transfer, and storage protocol as well of our server and data submission web tool.

This effort has resulted in several key documents:

Extensive research plan and associated progress report for Q1 FY 2017

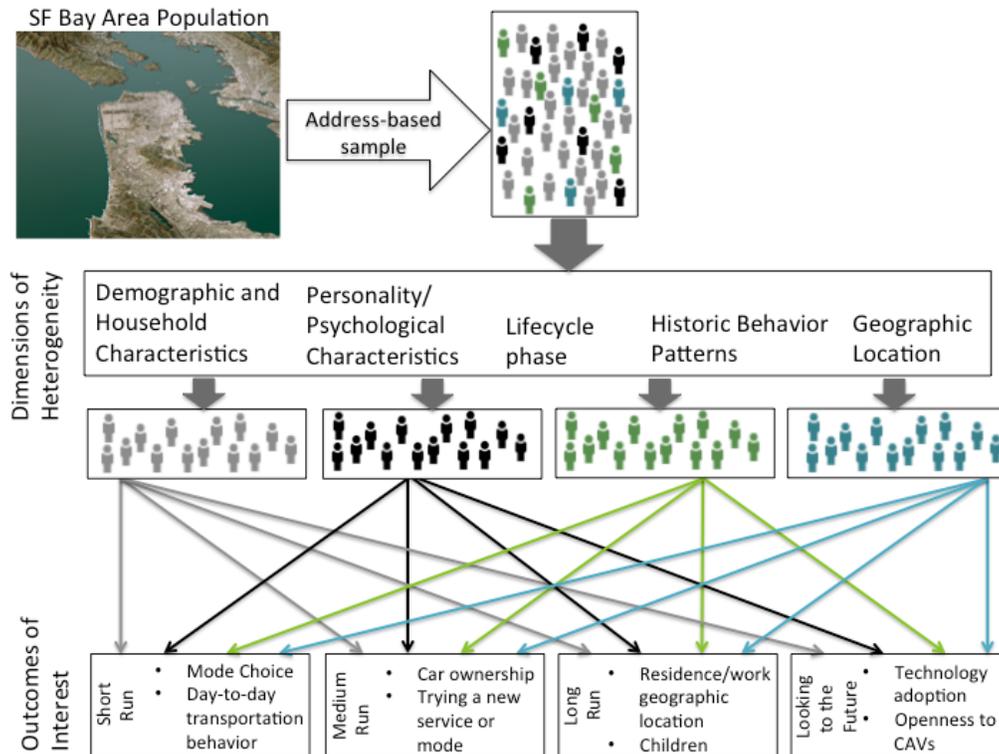


Figure III.1-1 - Research map for WholeTraveler

An Overview of Technologies for Individual Trip History Collection

This report includes a comprehensive review of all currently available types of fine-grained location data (FGLD). The report discusses the appropriateness of these various techniques for different applications. Particular focus is applied to appropriateness of different FGLD options for application in the WholeTraveler survey effort.

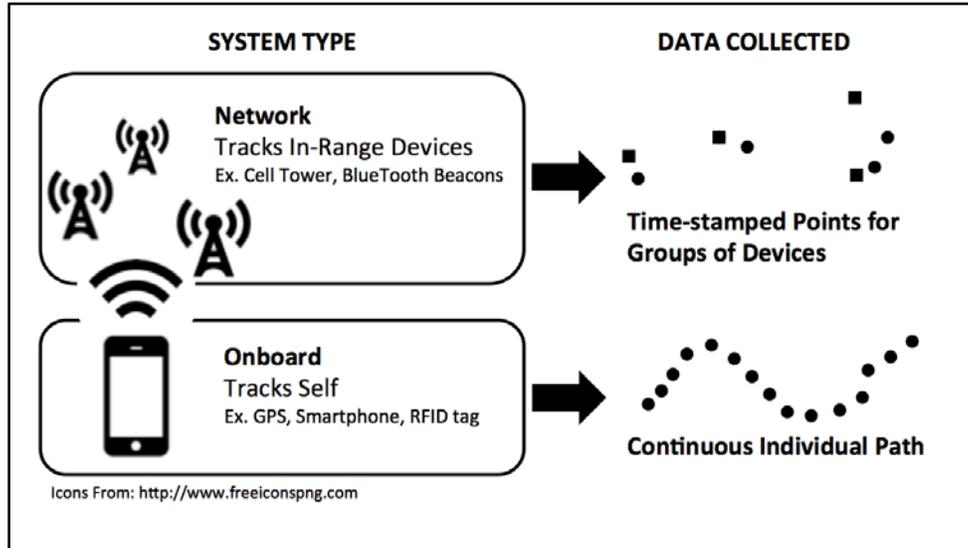


Figure III.1-2 - Fine-Grained Location Data System Types

Table III.1-1 - Common Location-Based Smartphone Applications

Genre	App	Android	iOS	User Access to FGLD	Limitations
Maps & Navigation	Google Maps	Yes	Yes	Export File	Google Account Sign In, Must Enable Location History
Maps & Navigation	Apple Maps	No	Yes	View Only	Point Locations Only, No Trip Details
Maps & Navigation	Waze	Yes	Yes	Export File	Car Trips Only
Transportation	Uber	Yes	Yes	View Only	Rideshare Trips Only
Transportation	Lyft	Yes	Yes	View Only	Rideshare Trips Only
Activity Tracker	Moves	Yes	Yes	Export File / API	
City Guide	FourSquare	Yes	Yes	Export File / API	Point Locations Only, No Trip Details
Fitness	RunKeeper	Yes	Yes	Export File	Pedestrian Trips Only, Manual Trip Start/Stop
Fitness	Strava	Yes	Yes	Export File	Pedestrian Trips Only, Manual Trip Start/Stop
Fitness	MapMyRide	Yes	Yes	Export File	Pedestrian Trips Only, Manual Trip Start/Stop

Energy and Transportation Behavior: Review and a Framework for Analysis

This was a review of relevant published research on behavioral factors associated with emerging transportation technologies (EV, CAVs, shared mobility, e-commerce), and identified gaps which WholeTraveler will address.

	Autonomous vehicles	EVs or electrification (includes BEVs, PHEVs)	Shared modes (includes carshare, rideshare, bikeshare)	e-Commerce
Demographics	Haboucha et al. 2017; Zmud et al. 2016	Axsen & Kurani 2014 Langbroek et al. 2017; Plotz et al. 2014; Wang et al. 2016; Ziefle et al. 2014	Chen & Kockelman 2016 Haboucha et al. 2017; Kopp et al. 2015; Prieto et al. 2017; Clauss & Doppe 2016	Rotem-Mindali 2010; Rotem-Mindali 2015; Zhou & Wang 2014; Cao & Mokhtarian 2012; Jiao et al. 2011
Influence or determinants (social, geographic, infrastructural, economic, etc.)	Childress et al. 2015; Sun et al. 2017 Haboucha et al. 2017; Zmud et al. 2016	Needell et al. 2016; Cai & Xu 2013; Axsen & Kurani 2014; Pontau et al. 2015 Seebauer 2015; Langbroek et al. 2017; Plotz et al. 2014; Wang et al. 2016; Ziefle et al. 2014; Jansson et al. 2017	Needell et al. 2016; Chen & Kockelman 2016; Cai & Xu 2013; Yanmaz-Tuzel & Ozbay 2010 Haboucha et al. 2017; Prieto et al. 2017; Zhou 2012; Clauss & Doppe 2016; Tang et al. 2015; van Exel et al. 2011	Zhen et al. 2016; Shao et al. 2016 Cao 2009; Cao et al. 2010; Ding & Lu 2017; Rotem-Mindali 2015; Zhou & Wang 2014; Cao & Mokhtarian 2012; Jiao et al. 2011; Louviere & Meyer 1981; Mokhtarian et al. 2011
Behaviors, choices, habits or attitudes toward transportation	Childress et al. 2015; Sun et al. 2017 Haboucha et al. 2017; Levin & Boyles 2015; Zmud et al. 2016	Axsen & Kurani 2014 Seebauer 2015; Langbroek et al. 2017; Nayum et al. 2016; Plotz et al. 2014; Wang et al. 2016; Ziefle et al. 2014; Jansson et al. 2017	Chen & Kockelman 2016 Haboucha et al. 2017; Kopp et al. 2015; Mishra et al. 2015; Prieto et al. 2017; Zhou 2012; Clauss & Doppe 2016; Tang et al. 2015; van Exel et al. 2011	Rosqvist & Hiselius 2016; Zhen et al. 2016; Shao et al. 2016 Cao 2009; Cao et al. 2010; Ding & Lu 2017; Rotem-Mindali 2010; Rotem-Mindali 2015; Zhou & Wang 2014; Cao & Mokhtarian 2012; Jiao et al. 2011; Louviere & Meyer 1981; Mokhtarian et al. 2011
Discusses technology but not in the context of these characteristic dimensions		Ensslen et al. 2017; Pontau et al. 2015	Yu et al. 2017	Hoogeveen & Reijnders 2002; Laghaei et al. 2016 Lee et al. 2017; Lenz 2005; Nagurney et al. 2001

DOES NOT INCLUDE ENERGY COMPONENT

INCLUDES ENERGY COMPONENT

Figure III.1-3 - Reviewed articles focused on emerging transportation trends, organized by content of characteristics dimensions and arranged by presence of energy component

Clustering life course trajectories: challenges with missing data and data types

This paper is an assessment of the performance of machine learning clustering algorithms (in particular using the edit-based distance measure through Optimal Matching) for clustering multi-dimensional data sequences in the face of data gaps and missing values. Also assessed is the sensitivity of treatment of missing data in the face of different data types (binary, nominal, or combined). The analysis uses the Panel Study of Income Dynamics data to create life course sequences for application of these clustering methods and validity assessments.

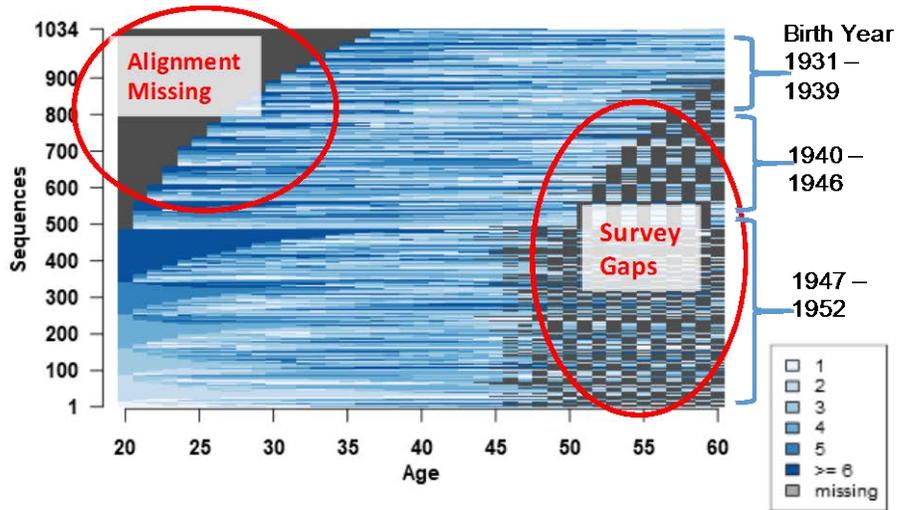


Figure III.1-4 - A plot family size sequence of all the individuals, to illustrate the missing value patterns that arise from survey gaps and missing segments after alignment by age

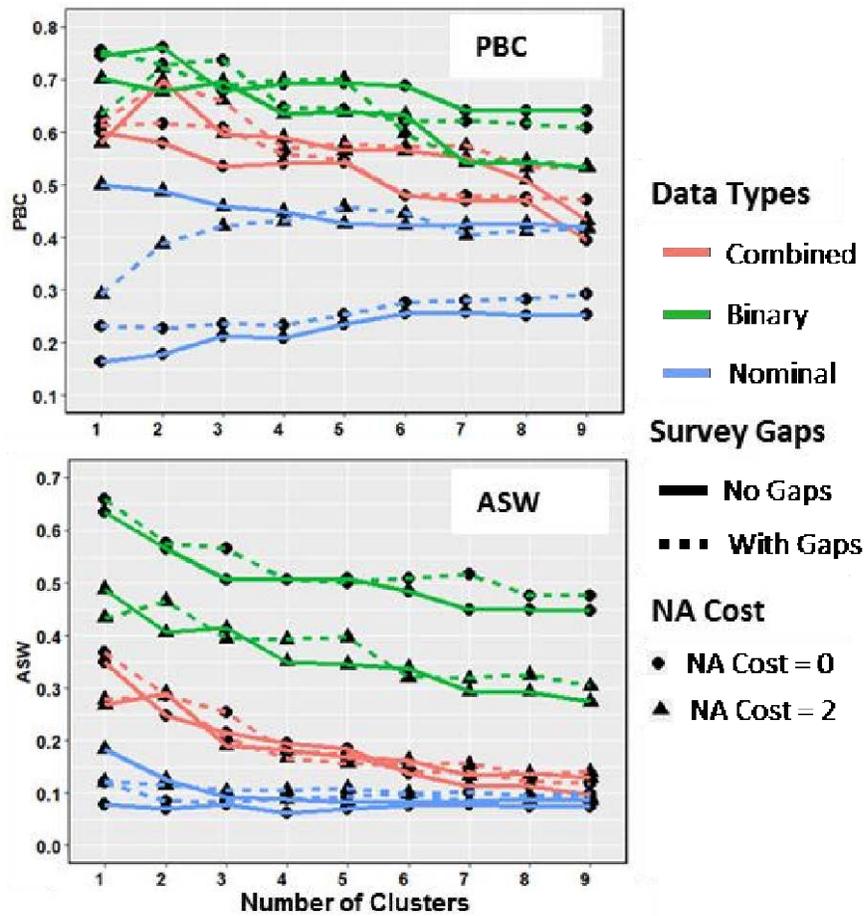


Figure III.1-5 - Point Biserial Correlation (PBC) and Average Silhouette Width (ASW) as a function of number of clusters, data types, and treatment of missing data

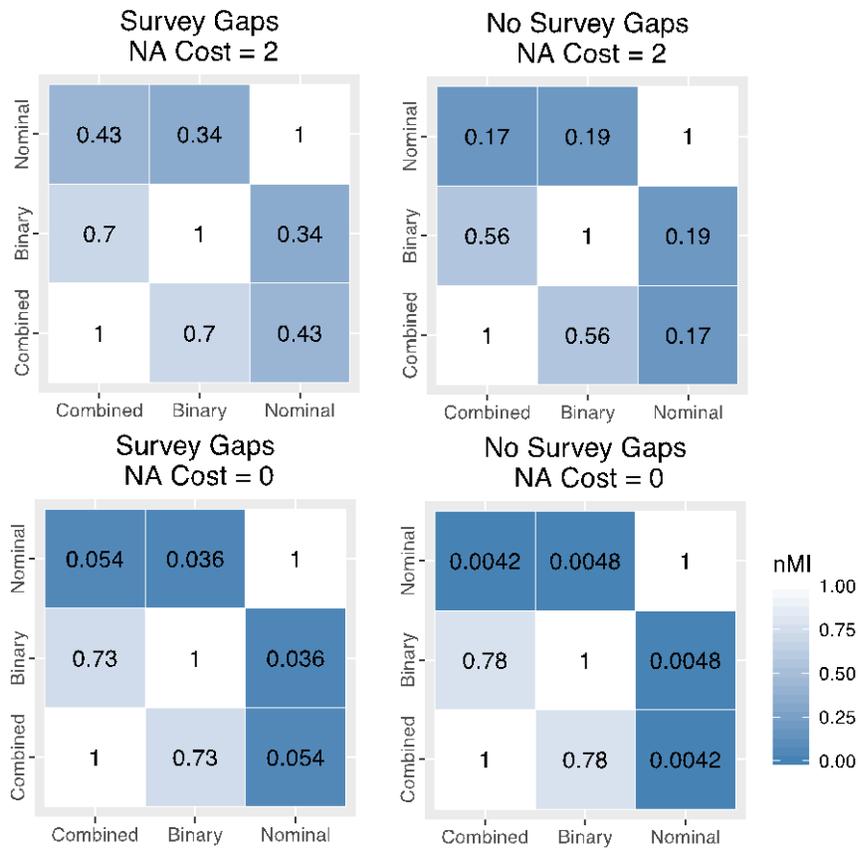


Figure III.1-6 - Normalized Mutual Information (nMI) between clustering solution derived from binary, nominal, and combined domains. Darker blue indicates greater differences between the pairs.

In addition, we’ve finalized the survey and implementation plan, which is ready to be launched as soon as final approvals are obtained.

Conclusions

We have conducted comprehensive background research to identify key gaps in current knowledge regarding important behavioral factors related to adoption and use of emerging transportation technologies and their energy implications for the transportation system. This background research, consisting of detailed reviews of locational data collection methodologies, related published literature, publically available survey datasets, and innovative machine learning methodologies for categorizing patterns in lifecycle trajectories, has informed the design of an innovative survey instrument. This two-phase survey has been carefully designed, programmed, and tested, and a rigorous implementation methodology identified and prepared. Pending final approvals, the survey can be launched. We have a detailed analysis plan and ambitious agenda of research the survey was designed to facilitate. Once data is obtained and cleaned, these efforts can get underway in earnest. In addition, the survey has been designed with feedback and input from multiple pillars in the SMART Mobility Initiative, and the data will ideally support multiple tasks within that initiative.

III.2 Travel Time Disutility in the Context of New Mobility Services [Task 2.1]

Paul N. Leiby, Principal Investigator

Oak Ridge National Laboratory
 P.O. Box 2008 MS6036
 Oak Ridge, TN 37830
 Phone: (865) 574-7720
 E-mail: leibypn@ornl.gov

Josh Auld, Principal Investigator

Argonne National Laboratory
 9700 S Cass Ave
 Lemont, IL 60439
 Phone: (630) 252-5460
 Email: jauld@anl.gov

David Anderson, Program Manager

U.S. Department of Energy
 Phone: (202) 287-5688
 E-mail: David.Anderson@ee.doe.gov

Start Date: November 1, 2016
 Total Project Cost: \$375,000

End Date: September 30, 2019
 DOE share: \$375,000

Non-DOE share: \$0

Project

One of the most important anticipated effects of new mobility services such as shared mobility and automation, and potentially the largest single benefit (e.g., Fagnant & Kochelman 2013, Speiser et al. 2014), is the reduction in the cost of travel time, through the reduction or elimination of the burden of driving for many road travelers. The disutility of travel time is likely to change as people take more trips without needing to drive, with the greater use of TNCs and the advent of automated vehicles. Households and individuals may alter their daily patterns of activities and time use as transportation options change, and they can sequence activities at home and away differently, or more easily multitask while traveling. It is now widely realized that if the cost or disutility of travel time diminishes, and there are many new options for travel time use, there could be major changes in the nature, frequency, and extent of road travel, with profound implications for vehicle miles traveled, energy use and emissions.

This project seeks to address this topic as one of the central issues for understanding and modeling future travel and transportation energy use. It will (1) Analyze the time-use and time valuation behavior of travelers using public transit and shared-mobility services, (2) Understand how time-use shifts for users of such services and, (3) Apply to CAV and shared fleet impact estimation.

Objectives

This project will (1) Analyze the time-use and time valuation behavior of travelers using public transit and shared-mobility services, (2) Understand how time-use shifts for users of such services and, (3) Apply to CAV and shared fleet energy impact estimation. The dual objectives of understanding time valuation and time use can be pursued jointly with related datasets and empirical analyses. Both patterns of time use (activities), and the value of travel time are essential inputs to the new travel demand and energy use models being developed in support of EEMS/SMART Mobility initiative. Such models simulate the travel activities of households, considering how travel activities relate to other daily activities and purposes, and considering how trip generation, route and mode choice may vary with the full costs of travel, including the important time cost/value component.

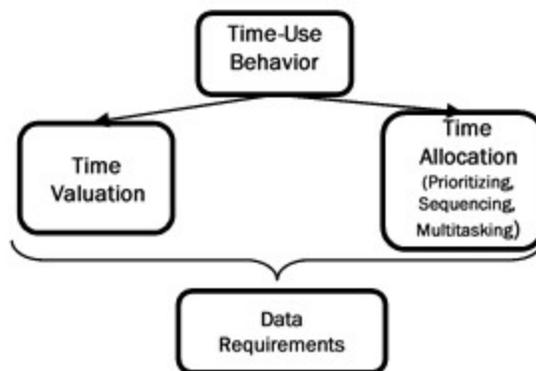


Figure III.2-1 - Travel time valuation and time allocation across activities may be estimated from related data on behavior and costs.

Approach

The primary approach is the empirical study of revealed preferences, using existing and newly-developing data on travel choices and time use. The first year approach centered on the identification and exploration of available large datasets on time use and travel choices, experimenting with ways of combining and supplementing them and applying three modern estimation approaches.

The work plan diagrammed in Figure III.2-2 below indicates a sequence of iterated data development and empirical modeling stages that seek to provide needed inputs to SMART Mobility travel demand/energy models such as POLARIS, BEMA, MA3T, and the Aggregated National Model of CAV Task 2

This project will provide a series of increasingly targeted estimates of time use patterns, tradeoffs among activities and travel, and travel time valuation that will provide activity choice and time value parameters needed by other modelers and analysts. First estimates are based on existing large survey datasets as data sources and methodologies are tested. Year 2 and 3 estimates will incorporate newly emerging travel activity datasets (such as those being developed in Northern California and selected other urban areas, and the new WholeTraveler Survey). These data provide greater resolution of activities and choices, and in some cases a better sample of modes (e.g., rail, transit, as well as shared car, taxi, TNC) that are useful proxies for the new mobility options and automated vehicles of interest.

Project Partners are:

- Taha Rashidi, University of New South Wales (Sydney, Australia), Research Center for Integrated Transport Innovation, School of Civil and Environmental Engineering. (contributing to data development and testing, model estimation)
- Jonathan Rubin, Department of Economics, Director Margaret Chase Smith Center for Public Policy, University of Maine (contributing to travel time theoretical approaches and regional SP/RP surveys of driver behavior)

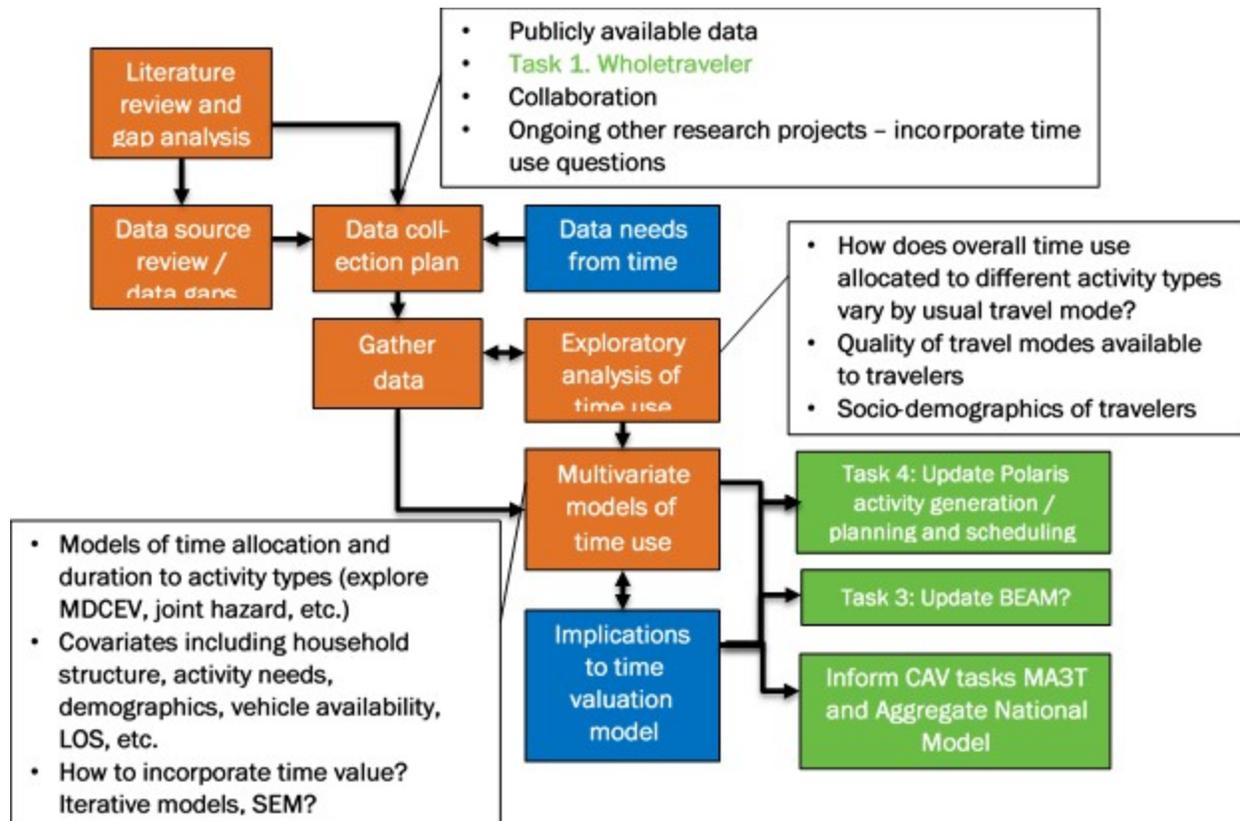


Figure III.2-2 - Project Planned Workflow

Results

In FY 2017, this project:

- **Completed a detailed literature and conceptual review, and drafted a data gathering plan.** The Qtr-2 report, *Analysis and Measurement of Time-Use and Time Value in an Era of Smart Mobility – 03/30/17*, provided a summary of previous literature on past time-use and value studies and empirical modeling methods. It identified the data available and likely data gaps, analysis methods, and a plan for collecting and initial analysis of data.
- **Undertook exploratory analysis with existing time-use & travel survey datasets**
- **Completed preliminary round, and 2nd round statistical analyses.** Focusing on Time Use Survey and Household Travel Survey datasets (e.g., CMAP, NHTS, ATUS, UKTUS), and the CES expenditure survey. Models of time allocation patterns and implied valuations were estimated. Three methods were applied and evaluated: Multinomial Logit (MNL), Multiple Discrete-Continuous Extreme Value (MDCEV), and a Contingent-Valuation-like method of Fosgerau (2006).

Identified data sources and needs.

Household travel surveys (CMAP, SEMCOG, ARC, etc.) were used, that provide detail on travel engagement, and mode usage. However alone they offer limited to no information on time use at locations (especially in home). In contrast, time use surveys (ATUS, MTUS, others) provide detailed time use by categories (TV watching, reading, socializing, etc.) and some information on travel patterns (time spent in various transport modes). Initial reviews identified the limitations of many existing dataset for reporting multi-tasking activities.

More detailed data on time use in the vehicle, and multitasking in general, was identified as a need. It was recognized that the UKTUS offers some information on this, and work with that survey was undertaken in Q4.

Data Needs

An important issue identified in the first round of estimations was that differences in the definition of activity-categories in different surveys can lead to significant differences in the estimated time use and time value patterns. The MDCEV estimation method (Baht 2005, Baht et al 2008) was identified as a promising method for estimating both time use allocations and tradeoffs. It can also be used to estimate time value provided suitable cost and financial budget data can be applied. The results of the first-round estimates were prepared as Transportation Research Board paper submission (Najmi et al. 2017) on the value of time considering market segments and activity pattern information

Two supplementary types of data were identified as necessary for the effective application of the MDCEV models to the CMAP travel survey data and for time value estimates with NHTS TUS datasets: reported or constructed data on unchosen travel modes and their attributes; and improved trip cost data. In FY 2017 Q3 and Q4 more complete cost data was constructed and added for the estimation. M. Javanmardi (ANL) prepared cost data for CMAP, through an intensive process, but one which can be replicated for other regions. These data on car usage, parking, tolls, and operating costs allowed improved estimates, but there are still some limits on their comprehensiveness. For large travel surveys, approaches were established to identify non-chosen travel alternatives for the trip (using choices by others, and using trip information from trip mapping services such as Google Maps) and for determining some of their attributes (mode, cost, time, etc.). Substantial empirical progress was made by the UNSW team. Newer estimates developing several mode choice models (binary for auto and transit) using CMAP data to estimate VOT for different trip purposes, times of day, education levels, age groups etc. are in development will be drafted in FY 2018 Q1.

Progress in Time and Use and Value Model Testing

A range of modeling approaches were developed and tested on the 5 main datasets being used. As one example, Table III.2-1 below illustrates the application of a more standard MNL-based calculation of the value of travel time based on estimated marginal utility and cost. It shows how a range of demographic and trip conditions (purpose, time of day, etc.) influence the relative valuation of time, and the sharp divergence between the value of time in auto versus transit.

Table III.2-1 - CMAP Data Analysis – VOT Marginal Utility estimation.

Attribute	Subgroup	Number of Samples	Goodness of Fit (ρ^2)	VTT (\$/Hr) Auto	VTT (\$/Hr) Transit
Arrival hour	6	2009	0.6416	25.9	3.1
Arrival hour	7	4876	0.5622	31.1	7.4
Arrival hour	8	5881	0.5008	41.6	6.9
Arrival hour	14	5072	0.7684	41.1	2.1
Departure Hour	11	3959	0.7352	37.6	5.6
Departure Hour	17	6642	0.5898	53.8	13.5
Departure Hour	18	4983	0.6683	82.3	12.1
Departure Hour	21	1648	0.7095	15.4	1.6
Departure Hour	23	443	0.7403	16.3	0.5
Destination CBD	Yes	71881	0.6999	2.8	7.5
Trip purpose	Work/Job	10062	0.4374	38.2	4.8
Trip purpose	Change type of transportation/transfer	204	0.3841	2.2	11.8
Age Group	18 -30	6044	0.5019	26.1	1.6
Gender	Female	39971	0.6296	20.4	0.3
Household size	2 persons	26271	0.6289	22.0	4.8
Homebased	No	27480	0.5979	70.8	5.1
Race	White	30588	0.6346	15.9	4.4
Race	Black/African American	5942	0.3886	12.9	2.1
Work	Yes	14363	0.4886	47.7	5.0

Work Underway in FY 2017Q4 and into FY 2018

Other model estimates were underway in Q4 and will be written up in early FY 2018

- CMAP Data Analysis – Direct estimation of VOT: In contrast to previous work where several models were developed for different demographics or trip purposes, this formulation estimates value of time as a function of explanatory variables.

- Application of the MDCEV method to 4 different datasets (NHTS, ATUS, UKTUS and CES (travel, time use, expenditure),
- Exploration of UKTUS multi-tasking data

Conclusions

The estimations and datasets assembled to date provide confidence that revealed preference estimates can be constructed for a range of relevant time use tradeoffs and time valuations over a variety of travel modes, conditions, and individual characteristics. Initial work applied a (singly) constrained MDCEV to time use data, accounting for the individual's time constraint. These results give us insights about the tradeoff between times spent for different activities. With further development or identification of travel attributes and costs for non-chosen alternatives, a doubly constrained MDCEV can provide proper estimation of VOT from rich time use and travel datasets.

Major findings from the MDCEV models include

1. Relatively comparable datasets, even if collected in the same year (2009 NHTS vs 2009 ATUS) result in different results with regard to how people budget their time.
2. Spatial transferring models can be quite misleading even if the structure of datasets are similar (ATUS vs UKTUS).
3. Creating a unified dataset where time and cost budgets are available is crucial for estimation of VOT. Expenditure/cost is a major missing factor in time-use / travel surveys. Data fusion, collation or synthesizing techniques (e.g., of HTS data and expenditure data) should be employed to complement what is missing.
4. Systems for categorizing activities can be inconsistent, and should be carefully considered.
5. Results demonstrate crucial importance of consistent estimation of time usage

Next Steps on Time-Use Patterns and Trade-offs

1. Seek to use estimated time use patterns (for a range of non-travel activities) to understand travel behavior. Breaking out travel as an activity in time-use survey information will be informative, but work is needed to resolve issues of numerical stability/convergence of estimation depending on grouping of activity categories
2. Refine structuring of the MDCEV activity categories, within and across datasets, Seek to identify activities that can be undertaken in vehicles (particularly CAVs, as well as trains and shared-autos), explore different activity choice mixes with new mobility options.
3. Aggressively pursue and focus on new and selected supplementary data to improve estimates. Particularly, focus on including / emphasizing data with closer AV proxies (Rail, taxi, shared-car, transit, TNC). Investigating FTA – Transit Rider Stated Preference Intercept Survey.
4. Pursue follow-on survey by partner Univ. Maine regarding Attitudes and Behavior with AVs, including proposed extensions to quantify time use/value
5. Seek and apply improved cost data and develop AV-relevant VOT estimates from a doubly-constrained MDCEV.

Key Publications

1. Report: "Analysis and Measurement of Time-Use and Time Value of Travel in the context of Emerging Mobility Technologies, Report 1: Purpose and Plan For Data Gathering," 3/31/2017, Paul N. Leiby (ORNL), Joshua Auld (ANL), Taha Rashidi (Univ. New South Wales), Jonathan D. Rubin (Univ. of Maine)

2. “Rethinking the Value of Time for an era of new mobility options,” Aug 1, 2017, Ali Najmi, Mohammad Nurul Hassan, Taha Hossein Rashidi, Rico Krueger, Joshua Auld, Mahmoud Javanmardi, Paul Leiby submitted for review, in revision.

III.3 TNC Services impacts on Travel Behavior and Energy Use [Task 2.2]

Alejandro Henao, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-2948
E-mail: Alejandro.Henao@NREL.gov

Tom Wenzel, Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road, 90R2000
Berkeley, CA 94720
Phone: (510) 486-5753
E-mail: TPWenzel@lbl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: May 1, 2017

End Date: September 30, 2019

Total Project Cost: \$900,000

DOE share: \$900,000

Non-DOE share: \$0

Project Introduction

Transportation Network Companies (TNC) or ride-hailing services such as Uber and Lyft are becoming a popular alternative to conventional modes of personal transportation. However there are scarce data and little research conducted to understand travelers' choice of this transportation mode and impacts on travel behavior and energy consumption. This task will analyze existing data regarding TNCs to better understand how travelers are currently using these services, and to provide inputs for travel activity models used in other pillars (e.g., BEAM and POLARIS) to test the sensitivity of energy use.

Objectives

The main objective of this task is to estimate the effect of TNC services on specific measurements related to energy use including vehicle ownership and vehicle miles of travel. This will enable the SMART consortium to estimate both the short- and long-run system energy impacts of large-scale TNC deployment using travel activity models developed under other SMART tasks. There were two major activities under this task in 2017:

- Begin assembling data to examine the relationship between the entrance of TNC services across different markets in U.S. cities and personal vehicle registrations; and
- An initial exploratory analysis of a database of individual rides provided by a TNC in Austin Texas.

We also continue to coordinate with other SMART pillars to develop a TNC research framework to identify data and analyze the energy consequences of widespread use of TNC services.

Approach

For the analysis of the relationship between date of entry of TNC service and vehicle registrations, we will run statistical regression models using a difference in difference approach. In FY 2017 we began assembling the following datasets:

- **Dependent Variable:** Vehicle registrations at the zip code level (2010-2016) using a national database of individual vehicle registrations provided by IHS Automotive (previously R.L. Polk & Company).
- **Independent Variable:** Uber and Lyft entry dates (Month/Year) focusing on two types of services (UberX/Lyft and UberPool/LyftLine). We are negotiating with the research and policy teams at Uber and Lyft to gather these datasets.
- **Controlling Variables:** Population, population density, economic variables such as personal per capita income and unemployment rate, etc.

We will use a difference-in-difference econometric model and develop an R code to run the statistical analysis.

We acquired and began analyzing a dataset of over 1.4 million individual rides provided by RideAustin, a non-profit TNC established in Austin Texas when Uber and Lyft left that market in May 2016. The data are from May 2016 to April 2017. The RideAustin dataset identifies each driver and passenger, so activity by individual drivers or passengers can be tracked over time. The database includes the location coordinates of each vehicle at several points along a particular ride, as well as the measured distance of the route taken while transporting a passenger. The database also includes the Month/Year, make, and model of all vehicles being used by RideAustin drivers.

We continue coordination with other SMART pillars (e.g., Urban Science, Task 2.1.4) to develop a research framework identifying major aspects of TNC services that will affect energy use, both increasing or reducing energy use. For example, reducing energy use by increasing vehicle occupancy with pooling services such as UberPool or LyftLine, decrease vehicle ownership moving from an habitual driver to a multimodal traveler, or concentrating VMT in fewer, high-mileage or electric vehicles. At the same time, TNCs can increase VMT and energy use with induced travel, drivers commuting long distances into urban centers, deadheading, or travel mode replacement shifting from more energy efficient modes (transit, bike or walk) to TNCs.

Results

In FY 2017 we began assembling the datasets to conduct the analysis of the relationship between date of TNC entry and vehicle registration, and began developing the R code to run statistical regressions. Figure III.3-1 and Table III.3-1 presents an example of the Polk dataset for the U.S. as a whole and a few examples at the state level including Colorado, California and New York.

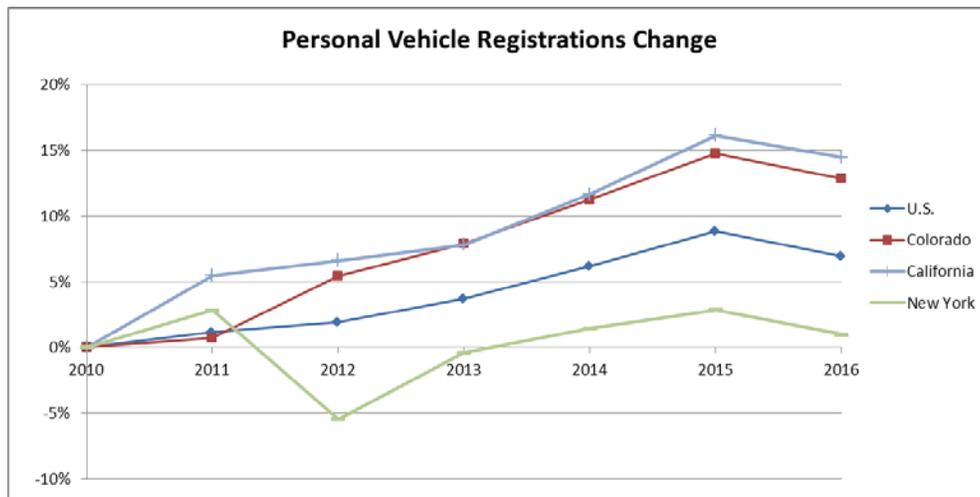


Figure III.3-1 - Personal Vehicle Registration Change (2010-2016)

Table III.3-1 - Personal Vehicle Registrations

U.S. or State Example	2010	2011	2012	2013	2014	2015	2016
U.S.	248,636,253	251,497,087	253,397,214	257,879,463	263,985,048	270,606,730	265,979,726
Colorado	4,408,786	4,441,029	4,647,253	4,757,126	4,904,433	5,058,381	4,974,930
California	26,369,967	27,813,231	28,112,422	28,427,320	29,445,359	30,621,730	30,181,098
New York	11,326,303	11,646,517	10,710,133	11,280,808	11,489,583	11,650,795	11,437,813

Initial analysis of the Ride Austin data allowed us to estimate factors of TNC service that affect energy use such as the increased VMT from deadheading miles TNC drivers travel between providing rides to customers. We estimated that RideAustin drivers travel 20% more miles just to reach their riders; and that drivers traveled an estimated 35% more miles between the end of a ride and the start of the next ride (including the distance traveled to reach the rider who requested the ride), even for rides within 20 minutes of each other. The estimated distance driven by a driver between rides is nearly double that of the measured distance between when a driver accepts a ride and reaches his/her rider, suggesting that RideAustin drivers are not parking their vehicles but are driving or circling while awaiting their next ride request, similar to conventional taxis. We hope to obtain data on individual trips provided by conventional taxis in Austin to compare the rate of deadhead miles in taxis to those driven by RideAustin drivers.

We began an analysis of the start and end locations of rides provided by RideAustin drivers; about 20% of all rides either began or ended at one of nine major locations: the Austin airport, the State Capitol, City Hall, convention center, UT campus, Rainey and Sixth Street entertainment areas, and the Omni and Westin Hotels in downtown Austin. The airport accounted for 6% of all destinations, and 3% of all origins; these rides averaged 12 miles in distance, compared to the average of 4 miles for all other rides provided. The hourly distributions of the rides provided varied by origin or destination; rides to or from the airport were distributed fairly equally throughout the day, whereas rides to the entertainment areas were concentrated in weekday evenings (and rides from those areas concentrated very early in weekday mornings). In FY 2018 we plan to analyze the locations of the starts and ends for the remaining 80% of rides provided. We plan to compare the locations to transit routes in Austin, from General Feed Transit Schedule data. We plan to infer whether riders shifted from a transit trip to a RideAustin ride. We also plan to examine rides provided to or from light rail stations in Austin.

In FY 2018 we will assign rated fuel economy values to the vehicles driven by RideAustin drivers, based on their year, make and model, using EPA's Fuel Economy Guide. We can then compare the average fuel economy of vehicles driven by RideAustin drivers with that of all vehicles registered in Austin, using a database of multiple years of registration data obtained for another project, to estimate whether shifting a trip from a private vehicle to a RideAustin vehicle reduces energy use.

Finally we have requested additional data from RideAustin to complement the analysis (e.g., data since April 2017); the address or zip code of the drivers, in order to estimate the energy use from drivers commuting into Austin to start driving for RideAustin; and any information on the fraction of rides or VMT that are shared by strangers pooling their travel.

Conclusions

Both the analysis of the relationship between date of TNC entry and vehicle registrations, as well as that of the RideAustin ride data, are ongoing; no conclusions are available as of this time.

III.4 Factors influencing PEV charging behavior [Task 2.3]

Zhenhong Lin, Principal Investigator

Oak Ridge National Laboratory
2360 Cherahala Blvd
Knoxville, TN 37932
Phone: (865) 946-1308
E-mail: linz@ornl.gov

Yutaka Motoaki, Principal Investigator

Idaho National Laboratory
2525 Fremont Ave
Idaho Falls, ID 83402
Phone: (208) 526-3752
E-mail: yutaka.motoaki@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2017

Total Project Cost: \$275,000

DOE share: \$275,000

Non-DOE share: \$0

Project Introduction

This task aims at understanding what factors influence how PEV drivers choose to charge their vehicles at the charging event level by explicitly considering both vehicle, infrastructure and traveler factors, such as vehicle range, charger power and travel patterns. The goal of the model is to inform about the medium and long-term implications on electrification, grid impact and energy consumption.

Objectives

The objective is to develop a charging decision model that links relevant factors to charging decisions and evaluate the collective effect of individual decisions at the regional and national levels

Approach

A cumulative prospect theory (CPT) based charging behavior model is developed (see Figure III.4-1), considering travelers risk attitudes, trip characteristics and charger attributes.

Results

A numeric example is presented in Table III.4-1 to illustrate how the model parameters impact the charging probability of different drivers. Assuming the following scenario:

Arrival SOC = 50 miles (mean range = 50 if not charge)

Expected travel distance to the next charger = 35 miles

Charging can add 20 miles (mean range = 70 if charge)

Base case (Driver 0) uses default parameters from the literature or empirical data of the general population

Driver 1-8: change one parameter at a time

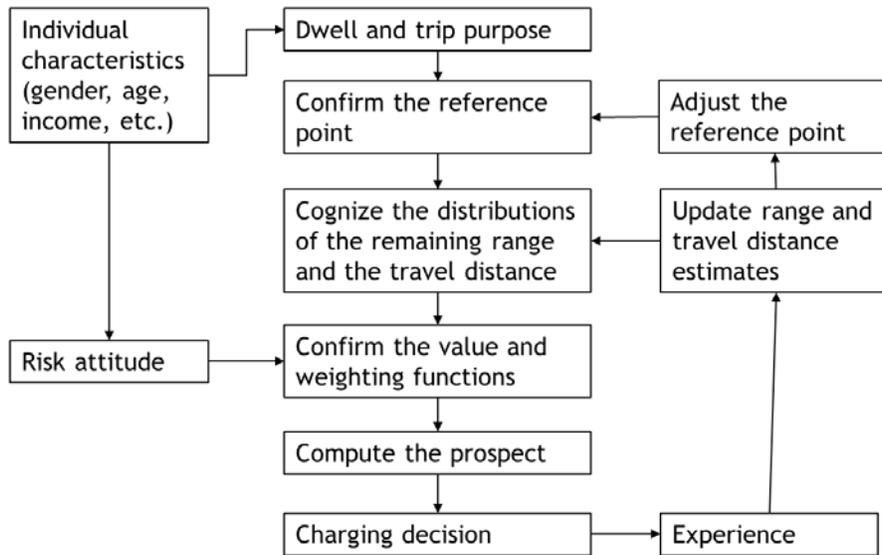


Figure III.4-1 - CPT Based Charging Behavior Model Framework

Table III.4-1 - The impact of model parameters on the charging probability

Driver #	x_0	A	β	λ	γ	δ	σ_r	σ_d	Charge prob.
Driver 0	10	0.88	0.88	2.25	0.6	0.69	10	10	27%
Driver 1	15								61%
Driver 2		0.6							67%
Driver 3			0.6						11%
Driver 4				4					68%
Driver 5					0.4				74%
Driver 6						0.4			73%
Driver 7							15		82%
Driver 8								15	82%

Conclusions

Based on the literature and empirical data, a set of factors influencing charging decision is identified, including (1) driver's socioeconomic characteristics, such as income, age, gender, and education, EV experience, home and work charging cost/availability; (2) dwell and trip characteristics, such as familiarity and cost of using the charging facility, activity at the dwell location, and characteristic of next trips; (3) charger characteristics, such as cost, familiarity, and convenience. These factors can be captured by the reference point and other CPT parameters, variability in the travel distance, and variability in the remaining range.

III.5 Travel Behavior Simulation Modeling – MATSim / BEAM [Task 3.1]

Anand R. Gopal, Principal Investigator

Lawrence Berkeley National Laboratory
1 Cyclotron Road MS 90R2121
Berkeley, CA 94720
Phone: (510) 486-5844
Email: argopal@lbl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2017

Total Project Cost: \$450,000

DOE share: \$450,000

Non-DOE share: \$0

Project Introduction

The SMART Mobility consortium has set out to answer a set of far-reaching questions about the future of mobility systems and their impact on transportation sector energy consumption. This highly ambitious effort is also founded on the idea that a systems modeling approach is critical to analyzing the inter-dependent impacts of changes to transportation behavior and technologies.

One key example of the inter-related impact of behaviors, technologies, and system level outcomes is induced demand. As technology enables new and existing transportation services to serve demand more efficiently in terms of energy, time, and cost, then more people will use those services. As demand for new and improved services increase, the gains in efficiency will be marginally eroded until a new system equilibrium is established that accounts for interactions between traveler preferences and the capacity of the system.

Traditional dynamic traffic assignment simulation models (DTA) are designed to facilitate the analysis of hypothetical changes to the transportation system. This typically means adding new capacity to the road network (e.g., by adding lanes). These approaches tend to use static representations of demand (origin/destination matrices) that ignore the continuity of travelers over the course of a day (i.e., they represent unconnected trips instead of individual activity patterns) or the details of system supply such as the movements of transit vehicles, taxis, or ride hailing vehicles.

Traditional DTA's are therefore ill-equipped to enable systems analysis that can capture many of the newly complicating features of the emerging transportation sector. For example, modern discrete choice analyses of traveler preferences now capture nuanced heterogeneity in traveler preferences, which are difficult to holistically embed in a traditional DTA model. Other traveler behaviors such as car-pooling and multi-modal trip planning via transit cannot be captured through DTA other than by making broad, high-level assumptions about their ultimate effect on trip distributions. Finally, as transportation network companies (TNCs) innovate in providing mobility services in a multitude of new ways, a simulation platform that doesn't represent the detailed operations of these service will be incapable of projecting their benefits and impacts before they've been fully integrated into the market.

In this task, we have embarked on a much more comprehensive approach to analyze the transportation system. We are employing agent-based modeling to simulate the behaviors of individual travelers as they engage with the system, allowing us to represent traveler heterogeneity and the detailed operations of mobility services (including transit as well as TNCs). Our initial and primary focus is on mode choice, as this can have dramatic impacts on the energy footprint of the transportation system.

Objectives

The objectives of Task 3.1 are as follows:

- Enhance and extend BEAM (the Framework for Behavior, Energy, Autonomy, and Mobility) to enable scalable simulations of the increasingly dynamic and inter-dependent transportation system.
- Apply BEAM to one or more urban regions.
- Conduct model calibration to ensure BEAM makes robust predictions of system level outcomes such as traffic patterns, modal splits, and TNC operations.
- Use the calibrated model to conduct normative analyses that assess the potential to leverage knowledge about human behavior to incentivize beneficial system outcomes. e.g., to what extent can cross-subsidies or other incentive schemes reduce the energy use of the system?

Approach

Our approach involves four main sub-tasks:

1. **Enhance and extend BEAM (the Framework for Behavior, Energy, Autonomy, and Mobility) to enable scalable simulations of the increasingly dynamic and inter-dependent transportation system.**

The BEAM Framework acts as a plug-in to the MATSim model. MATSim features a modular simulation engine that employs an iterative scheme and co-evolutionary optimization to achieve user equilibrium in the

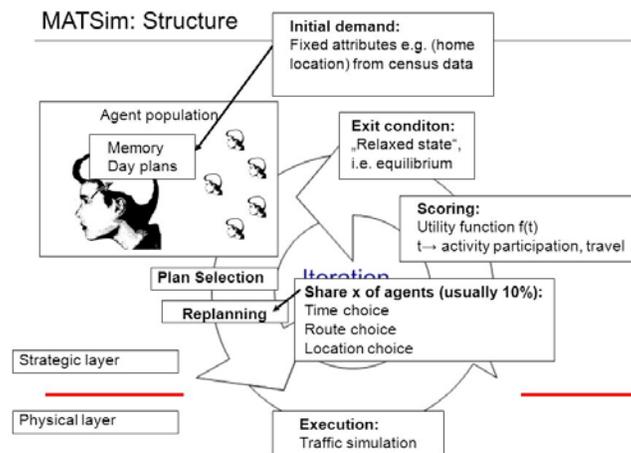


Figure III.5-1 - MATSim iterative structure (Horni, 2017).

transportation system. In other words, the simulation of a typical weekday is repeatedly executed and the individual agents are given the opportunity to modify their travel plan for the day after each round. The basis for modifying their plan and selecting from a learned history of old plans depends on the scoring step, which evaluates a utility function. In its most basic form, the utility function yields positive utility (with decreasing marginal returns) for engaging in one's activities and negative utility for traveling. But the utility function is extensible and can be modified to include any new events that are relevant to the traveler's experience. For example, range anxiety experienced by the driver of a battery electric vehicle can be implemented as additional disutility in the function.

BEAM extends the scoring and replanning capabilities of MATSim to allow travelers to exhibit adaptive behaviors within the simulation day, rather than between days. This focus on the dynamic interactions between agents and the mobility system during the day enables BEAM to capture the detailed operations of mobility

services like transit and TNCs while simultaneously allowing these operations to influence traveler behavior through the mode choice mechanism.

BEAM is also designed for scalability. Though the MATSim framework is highly extensible, only a limited features set (mostly traffic flow) has been optimized for computing at massive scale (full sample of cities with millions of agents). BEAM has been designed from the ground-up to enable large scale simulations through use of the actor model of computation.

The actor model (Hewitt et al, 1973) is a formalism for concurrent programming which fully encapsulates units of computation as “actors” and prescribes a system of communication between the actors (messaging) which simplifies reasoning about control flow and memory access within actors (by making it akin to programming for single-threaded execution) while simultaneously abstracting the management of concurrent execution. Designing BEAM within the actor model allows it to make use of libraries (specifically the Akka library developed by Lightbend, Inc.) that handle the challenges of optimizing multi-thread execution so that developers and users of BEAM can focus on model development rather than model scaling.

BEAM Framework

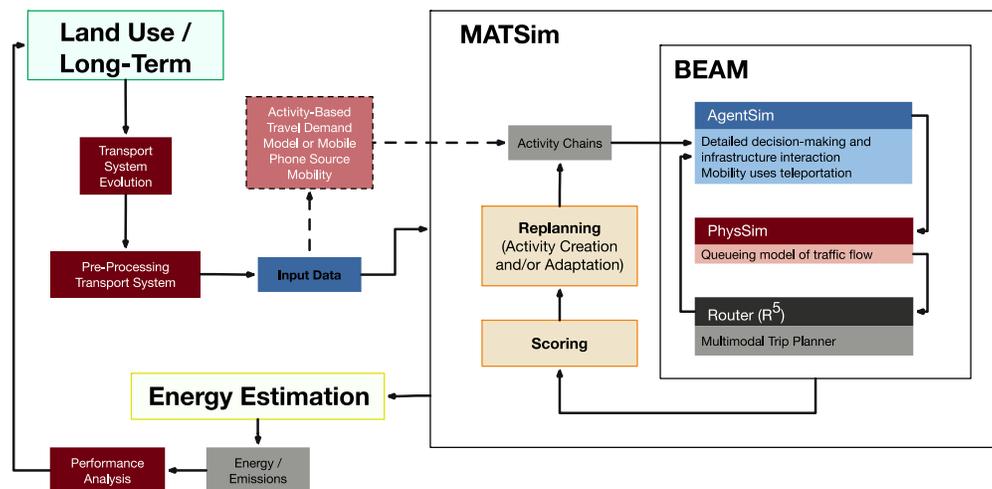


Figure III.5-2 - Master plan for the BEAM Framework. In FY 2017, the focus has been on development and integration of the BEAM modules within MATSim.

The BEAM mobility simulation is divided into three primary components: the AgentSim, the PhysSim, and the Router. The AgentSim is where agents plan and execute their mobility for the day. To accomplish this, agent’s make extensive use of the Router for trip planning. The Router is based on the R5 (Rapid, Realistic Routing on Real-World and Reimagined Networks) by Conveyal, the makers of OpenTripPlanner. The R5 engine features fast multimodal routing which can be used for point to point routing as well as accessibility analysis. As vehicles in the AgentSim move through the road network, they generate events which are transferred to the PhysSim, which executes a traffic flow simulation from the standard MATSim framework, but does so decoupled from the AgentSim in order to facilitate parallel processing.

Within the AgentSim, travelers execute a mode choice model which evaluates the utility of modal alternatives and then samples from the resulting distribution. In the preliminary implementation of BEAM, several mode choice models have been developed and used for various purposes. The results below were creating using a simple multinomial logit model which has four alternatives: DRIVE, TRANSIT, WALK, RIDE HAIL. Each linear utility function considers time and cost, with parameters chosen so the ratio is equivalent to the value of time assumed for the model run (e.g., our base scenario in the results below assumes \$18/hr). The transit alternative also includes the number of transfers as an independent variable in the utility function. When

travelers are faced with multiple alternatives that qualify as one of four outlined above, the best representative trip itinerary is used to evaluate the overall utility function for that mode and is used if that mode is chosen.

Finally, the outcome of the simulated day is characterized in terms of vehicle trajectories, allowing for post-processing to quantify the energy consumption of the system across space, time, mode, or other dimension of interest. Energy consumption estimates are currently based on fleet average EPA ratings. In FY 2018 we have proposed including more detailed models of energy consumption in partnership with NREL using MOVES.

2. **Apply BEAM to one or more urban regions, beginning with the San Francisco Bay Area.**

Based on previous work conducted by the Smart Cities Research Center at UC Berkeley and the Metropolitan Transportation Commission (MTC), we have focused our initial application development on the San Francisco Bay Area where we have a ready source of activity plans from the MTC Activity-Based Travel Demand Model (MTC, 2012). We sample from these 2.5M activity chains to any desired subset and combine the plans data with U.S. Census data to create synthetic populations with representative spatial demographics, including characteristics such as household size, number of cars per household, and income.

We use the R5 network loading capability to parse data from Open Street Map and as well as transit feed data from the 28 local transit agencies in the Bay Area to create the transportation network representation used for routing. Finally, we collected a database of transit fleet data which we use to assign transit vehicle types (e.g., diesel versus electrified buses) to the trips in the transit feed data.

3. **Conduct model calibration to ensure BEAM makes robust predictions of system level outcomes such as traffic patterns, modal splits, and TNC operations.**

This work will primarily happen in FY 2018, but we have already conducted preliminary calibration of the multinomial logit choice model to match aggregate observed modal splits in the Bay Area. Based on data available from the MTC, we have adjusted the intercepts of the utility functions of the four alternatives in the model described above to create the results presented below. In the coming months, we will expand our calibration work to cover the more advanced latent class choice model which has the advantage of yielding modality styles as an output of the simulation. See our Annual Deliverable for a more detailed explanation of this approach.

4. **Use the calibrated model to conduct normative analyses that assess the potential to leverage knowledge about human behavior to incentivize beneficial system outcomes.**

This work will occur in FY 2018-FY19. An early task in FY 2018 is to clearly define the range of analyses that will be conducted with the calibrated BEAM model. For example, to what extent can cross-subsidies or other incentive schemes induce shifts in travel among modes and reduce the energy use of the system?

Results

The results presented below represent a very preliminary example of the kinds of outputs and analyses that BEAM is capable of producing for the San Francisco Bay Area. Though we use a choice model that exhibits reasonable sensitivities to changes in modal alternatives (i.e., it is sensitive to trip time and cost), the calibration was preliminary and therefore the model has yet to produce robust agreement with observe data across all dimensions of interest. Nevertheless, these results are illustrative of the benefits of agent-based simulation modeling which can be observed with complete omniscience and therefore the system can be analyzed in a multitude of ways.

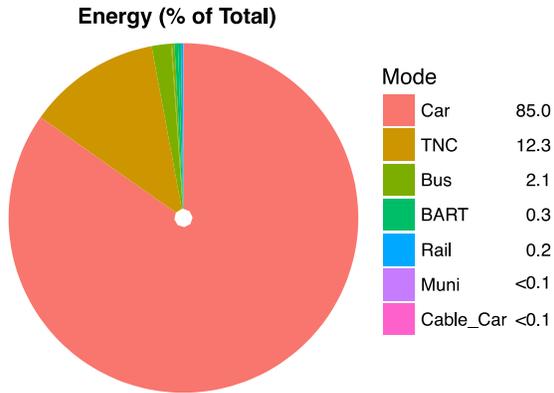


Figure III.5-3 - Total daily energy consumed by mode in the San Francisco Bay Area.

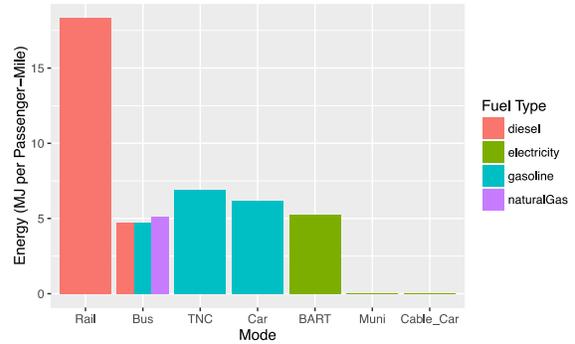


Figure III.5-4 - Energy consumption by mode and fuel type per passenger-mile in the San Francisco Bay Area. Rail is exceptionally high due to underutilization in the simulation (too few passengers). Rectifying this artifact will be a focus of future calibration work.

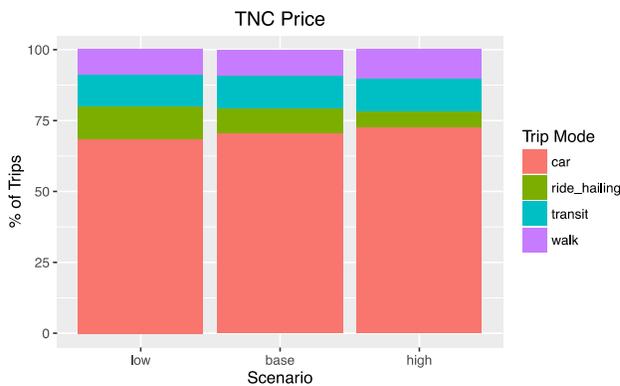


Figure III.5-5 - Modal splits are sensitive to price of TNC services.

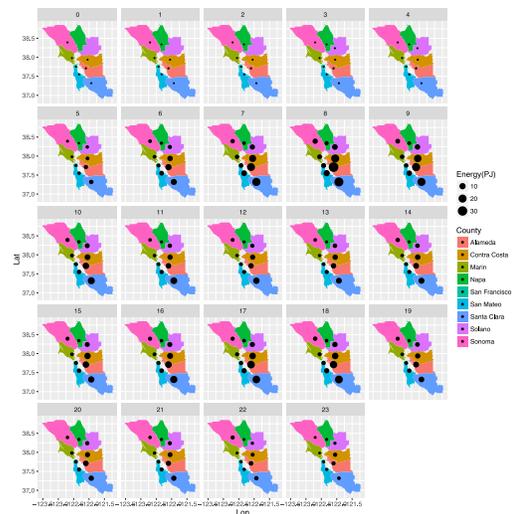


Figure III.5-6 - Energy consumption is quantified spatiotemporally for the San Francisco Bay Area.

Conclusions

In FY 2017, we have successfully enhanced the BEAM/MATSim simulation platform to achieve scalable, dynamic simulation capabilities that include all modes of travel and we have applied the model to the San Francisco Bay Area.

Key Publications

We have presented our ongoing work in the following venues:

1. SMART Mobility Modeling and Simulation Tools Workshop. Oak Ridge National Laboratory, November, 2016.
2. SMART Mobility / Smart City Challenge Coordination Workshop. Columbus, Ohio. December, 2016.
3. U.S. DOE Annual Merit Review. Washington, DC. June, 2017.
4. ITS World Congress. Montreal, QC. October, 2017.

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III.6 Travel Behavior Simulation Modeling—POLARIS [Task 4]

Joshua Auld, Principal Investigator

Argonne National Laboratory
 9700 South Cass Avenue, Building 362
 Argonne, IL 60439
 Phone: (630) 252-5460
 E-mail: jauld@anl.gov

Zhenhong Lin, Principal Investigator

Oak Ridge National Laboratory
 1 Bethel Valley Road
 Oak Ridge, TN 37831
 Phone: (865) 946-1308
 E-mail: linz@ornl.gov

David Anderson, Program Manager

U.S. Department of Energy
 Phone: (202) 287-5688
 E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2017

Total Project Cost: \$450,000

DOE share: \$\$450,000

Non-DOE share: \$0

Project Introduction

The transportation research clearly shows that potential changes in travel demand are a key driver of uncertainty regarding the overall impacts of future mobility in terms of energy use. In this task, we seek to extend the POLARIS model to better characterize mobility decisions under new mobility technologies and modes. The core behavioral modeling components of the POLARIS simulator will be enhanced to capture changes in short-term, mid-term, and long-term decision-making brought about by new technologies. We will use the updated POLARIS transportation simulation model to evaluate the energy and emissions outcomes of these new mobility technologies in the context of the Chicago metropolitan region.

Objectives

- Enhance the POLARIS simulation framework to incorporate the range of decision-making applicable to the scenarios of interest under Mobility Decision Science (MDS)
- Implement traveler behavioral models in POLARIS regarding vehicle choice, activity planning, mode choice and others that are sensitive to factors relating to future mobility scenarios
- Understand technological, behavior, and policy factors that affect shifts in fuel use and mobility
- Evaluate behavioral response due to future mobility, design policies, and model energy impacts
- Compliment MATSIM approach by testing in multiple regions using multiple approaches and modeling different behaviors; implement a joint calibration framework

Approach

The approach taken to achieve the objectives of the travel behavior simulation task involves implementation of various behavioral models developed as part of this research, other MDS tasks, or drawn from the literature. The models of key traveler behaviors are incorporated into the POLARIS agent-based modeling framework to evaluate sensitivities of the various behaviors to potential changes under various MDS scenarios. An overview

of the improvements to the core POLARIS model is shown in Figure III.6-1. The primary tasks under the travel behavior simulation project over the last fiscal year involved:

- Develop a vehicle choice framework along with a CAV technology choice model
- Modify/develop mode, location and timing choice models
- Develop and implement a telecommuting behavior module
- Enhance the POLARIS multi-modal router to handle intermodal trip-making behavior
- Study the impact of vehicle-sharing within households
- Perform case studies demonstrating energy impacts under behavioral scenarios

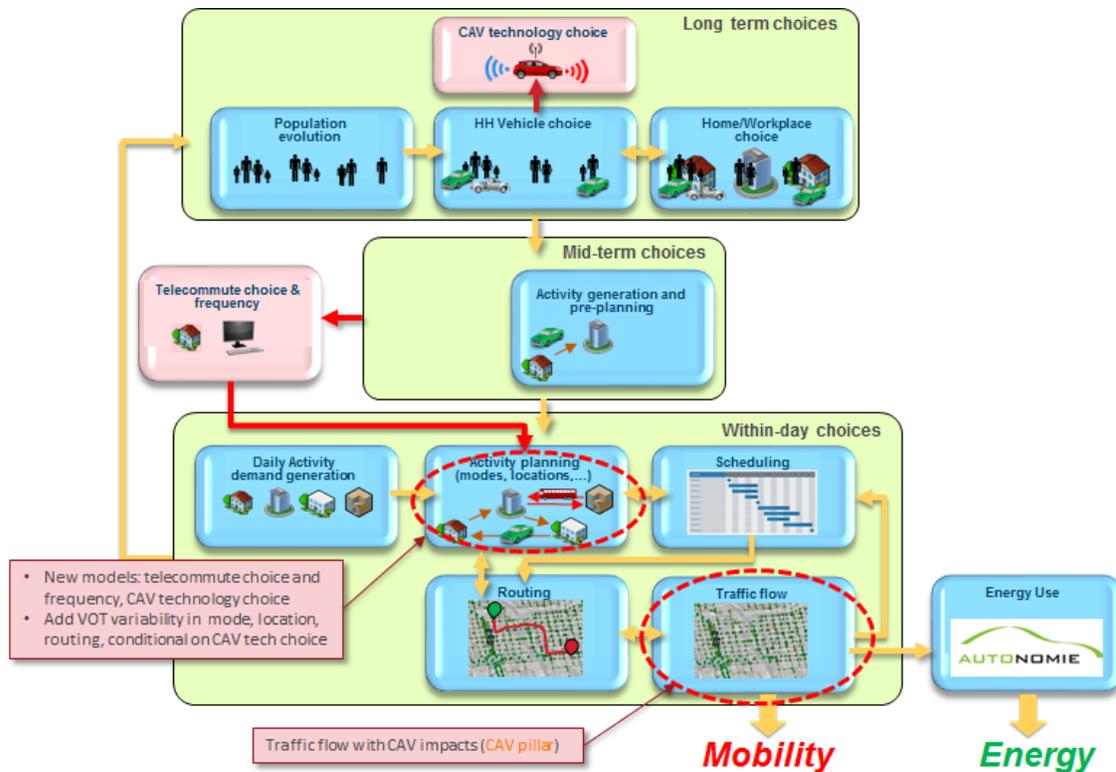


Figure III.6-1 - POLARIS Modeling Process with MDS Improvements Highlighted

The project requires significant inputs from other tasks and pillars and work includes a collaboration with a number of other laboratories and universities. Oak Ridge National Laboratory (ORNL) is supporting the vehicle choice task through integration with outputs from the Market Acceptance of Advanced Automotive Technologies (MA3T) model, while the University of Illinois at Chicago (UIC) has helped with estimation of the CAV technology choice models used to distribute CAV-enabled vehicles to the MA3T defined fleets in the simulation runs. The University of New South Wales (UNSW) and ORNL have made contributions on the Value of Travel Time (VOTT) change impact tasks through MDS 2.1 work. UIC has contributed to the estimation of an activity start and duration choice model and the development of the telecommuting behavior framework. All models, whether estimated at Argonne, through university or laboratory collaborators, or from the literature, have been implemented in POLARIS as agent-based behavioral modules controlled through external parameter files as seen on the POLARIS GitHub repository. The POLARIS-Autonomie simulator with the updated behavioral modules in place was then used to analyze the energy impacts for scenarios relating to telecommute policy changes, as discussed in the results section.

Vehicle Choice, Allocation, and Technology Selection Framework

The development of the vehicle choice/allocation framework in POLARIS started with the addition of the Vehicle_Agent to the POLARIS code and I/O framework. Vehicle agents are owned by individual households and have a set of characteristics including class, powertrain type, fuel use type, and automation and connectivity characteristics, which can be linked to pre-compiled Autonomie models. The vehicles are distributed geographically to households based on the household vehicle fleet size. Fleet size data are obtained from the population synthesizer and census inputs according to distributions drawn from Polk Vehicle registration data, MA3T market forecast data, or individualized household-level choice models (when available). The vehicles within the household are then allocated on a trip-by-trip basis using a first come, first served priority queue. The state of each vehicle, in terms of occupancy and location, is continuously tracked to constrain the subsequent vehicle allocations. When the vehicles are assigned to households, an advanced technology choice process is called on to determine if the vehicle is equipped with level 3 or level 4 automation technologies – information used in CAV analysis scenarios. UIC estimated the model based on locally collected, stated preference survey data (Shabanpour et al. 2017) and compared the model to one from the literature (Bansal et al. 2017). The survey included 1253 respondents who provided willingness to pay (WTP) information along with demographics; travel pattern information; and expectations, concerns, and attitudes toward technology and CAV. The model uses an extension of the ordered probit model, called the Random-Thresholds, Random-Parameters Hierarchical Ordered Probit (RTRP-HOPIT) model, to estimate how much each individual household would be willing to pay for each vehicle to contain the CAV technology. The extension to the ordered probit model allows for flexible thresholds in WTP levels, which can vary randomly to account for unobserved taste heterogeneity. The estimated WTP values are then converted to CAV market penetration by specifying the marginal cost of the automation technology and assuming that everyone with a WTP greater than the marginal cost has a CAV. As such this framework is not a model of market dynamics or a detailed market forecast simulation, but rather is a meaningful way to distribute CAVs to travelers for a given penetration scenario.

Behavioral Model Modifications and/or Estimation

Several of the core POLARIS behavioral models have been modified or estimated to ensure policy sensitivity to variables of interest under SMART mobility scenarios. The existing POLARIS mode choice and destination choice modules have been modified to allow for a flexible individual VOTT savings for each traveler, which can be updated based on the trip context (work trip, non-work, leisure, etc.) and the vehicle selected (CAV enabled, CAV level). The individualized VOTT measure then enters the utility functions for each choice model and alters the choice behavior of the traveler for the simulation. The VOTT changes are currently drawn from assumptions in the literature, but will be replaced with findings from the MDS 2.1 task by UNSW, Argonne, and ORNL. In addition to the mode and destination choice modules, a new joint start-time and duration model has been estimated in collaboration with UIC and is being implemented (completion is expected by first quarter of fiscal year [FY] 2018), for sensitivity analysis within POLARIS. The joint start-time duration model uses a discrete-continuous copula model, where the start time choice is estimated as a

hybrid regret minimization and utility maximization process, and the duration is modeled through a continuous log-linear model. Both models are linked through a Frank-copula formulation (Golshani et al. 2017). The start and duration both include individual and household demographic variables, activity-specific variables, planning and scheduling factors, and observed travel time and travel time variance for each time-of-day period. The extensive use of covariates endogenous to the POLARIS behavior simulator (travel time, time variation, activity flexibility, occupancy, etc.) should ensure that the model is sensitive to a variety of policy scenarios, which will be evaluated in FY2018.

Telecommuting Behavior Module

The choice of telecommuting is another key behavioral process of individual workers that is likely to change as connectivity and automation technologies in vehicles and elsewhere improve. A new module representing the choice of telecommuting for working individuals has been estimated and implemented in POLARIS and is called on after the workplace choice module. The current model is estimated as a Zero-Inflated Hierarchical Ordered Probit (ZI-HOPIT) using survey data collected from the Chicago Metropolitan Agency for Planning (CMAP). The zero inflation part of the choice process represents the choice of being a telecommuter or not, while the ordered probit part represents the frequency of telecommuting (ranging from never to daily). The model finds a significant relationship between telecommuting and occupation, schedule flexibility, workplace trip distance, and general socio-demographics. The choice and frequency telecommute model has been implemented as a parameterized POLARIS module with the parameters modifiable in a configuration file for scenario analysis.

Intermodal Routing Behavior

A significant update to the POLARIS routing module was also implemented allowing for heterogeneous, intermodal route selection. The newly developed time-dependent intermodal A* (TDIMA*) algorithm is a point-to-point shortest path algorithm recently developed at Argonne that includes driving, walking, biking, and all transit modes (e.g., bus, suburban bus, rail, commuter rail). For a given origin-destination pair and departure time, TDIMA* generates the shortest path based on the traveler's attributes, as well as the desired set of modes. The traveler may choose walking to transit, biking to transit, park-and-ride, kiss-and-ride, or using bike-share services along their path, as well as utilize Transportation Network Company (TNC) services such as Uber or Lyft. Finding the shortest path in an intermodal network is complex because the travelers have different perceptions of different legs of their journey. Many travelers perceive the value of time spent walking or waiting for a transit vehicle higher than the time spent in a transit vehicle. Moreover, there is an extra penalty associated with transfers beside the waiting time. Each additional transfer might incur a higher perceived penalty than the one before. To address these issues, the TDIMA* algorithm has traveler-specific weights for the time spent walking, biking, waiting, in a transit vehicle (sensitive to crowding), in a private car, in a cab, in a TNC vehicle, and progressive penalties for transfers. In a large-scale network such as the Chicago metropolitan region with over 50,000 nodes, 200,000 links, 340 routes, and 28,000 transit trips, the algorithm provides a point-to-point intermodal shortest path within 8 milliseconds. In FY 2018, the route generation using TDIMA* will be incorporated into the mode choice model in place of level-of-service skims, in order to have exact costs, constraints and model availability for each mode considered, including TNC and park-and-ride.

Within Household Vehicle Sharing

When simulating the travel behavior of a household with fully automated vehicles, there is a possibility of car-sharing between household members causing zero-occupancy vehicle (ZOV) travel miles. To analyze this possibility, we first study how many activities of different members can be served with minimum alterations to their schedules and with the minimum number of privately owned AVs, considering activity schedules, flexibilities, travel distances and so on. There are several trade-offs that need to be addressed. If the household has fewer AVs than it used to have conventional private cars, there might be adjustments in some activities (start time and/or duration), empty (ZOV) trips generated between activities to accommodate different household members or to avoid parking costs, and realization of some trips using outsourced services such as cabs, TNCs, or transit. Although the answer to this multi-factor problem is not yet known, it is known that the

outcome depends on the cost of driving an AV, the cost of owning an AV, the cost of parking, the fixed and variable costs of the outsourced services, and the imposed taxes on ZOV trips. To explore the issue further, we developed and implemented an optimization algorithm that can effectively maximize the total utility of a household under different cost assumptions for various travel factors, and possibly extend to non-household vehicle and ride sharing.

Results

The POLARIS-Autonomie simulator has been used over the past fiscal year to analyze a number of hypothetical scenarios relating to MDS and behavior. A set of scenarios was run to explore the impact of increased telecommuting on energy use. We varied a key behavioral parameter from the telecommute model—the percentage of workers with schedule flexibility offered by the employer—from the baseline of 12% up to 50% of all employees. The results, shown in Table III.6-1 and Figure III.6-2, demonstrate there is a slight energy reduction of 1.0% in fuel use for a 3.0 percentage point increase in teleworking. This occurs due to a vehicle miles travelled (VMT) reduction of 0.7%, while vehicle hours traveled (VHT) were reduced by 2.1%. The decreases show up as reductions in travel and fuel used along primary commuter corridors and increases in outlying suburbs as commuters travel more near home. Aggressive policies to increase telecommuting further can be explored over the next fiscal year.

Table III.6-1 - Telecommuting Policy Mobility and Energy Results

% Flex	% Teleworking	% Change in Activities	VMT Change	VHT Change	Fuel Use (MM gallons)
12%	2.6%	-	-	-	-
25%	3.6%	0.14%	-0.22%	-1.00%	-0.36%
50%	5.6%	0.22%	-0.69%	-2.09%	-0.97%

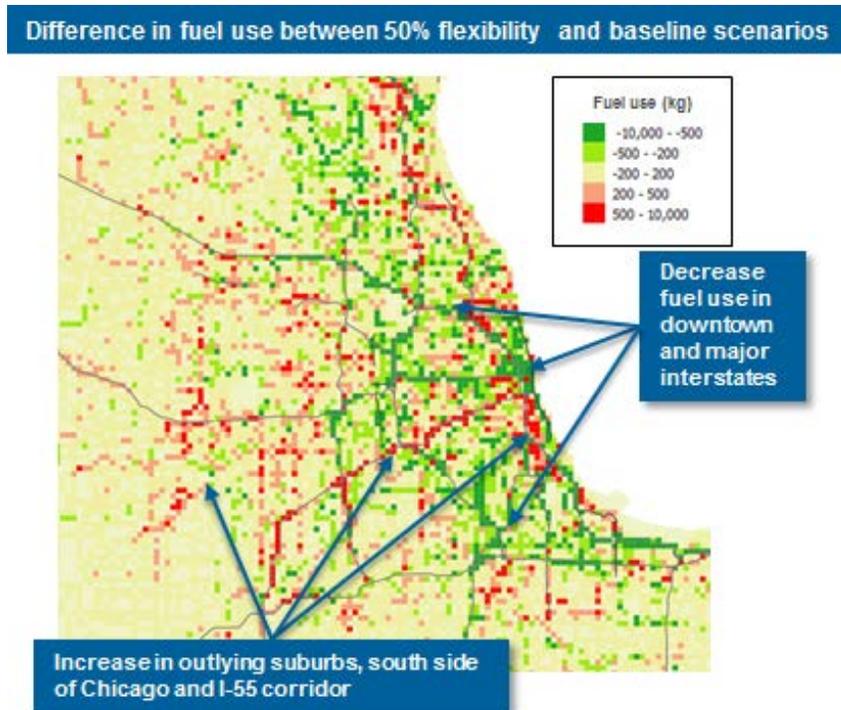


Figure III.6-2 - Change in Fuel Use in High Telecommuting Scenario Compared to Baseline

Validation testing for the intermodal time-dependent router has been performed to verify appropriateness for use in generating modal choice options and choice characteristics. The router behavioral parameters were tuned using an input data set derived from the Chicago household travel survey. We extracted a set of 556 intermodal trips (i.e., containing at least one non-walking leg in addition to the transit leg). The trips have been validated against the reported travel times and access-egress characteristics as shown in the Figure III.6-3. The routed intermodal travel times compare to the self-reported travel times with an R^2 of 0.61, and are in all cases shorter than travel times returned by various online trip routers, including Google Maps and the Chicago Regional Transit Authority trip planner, largely due to the ability to capture kiss-and-ride and park-and-ride trips more accurately.

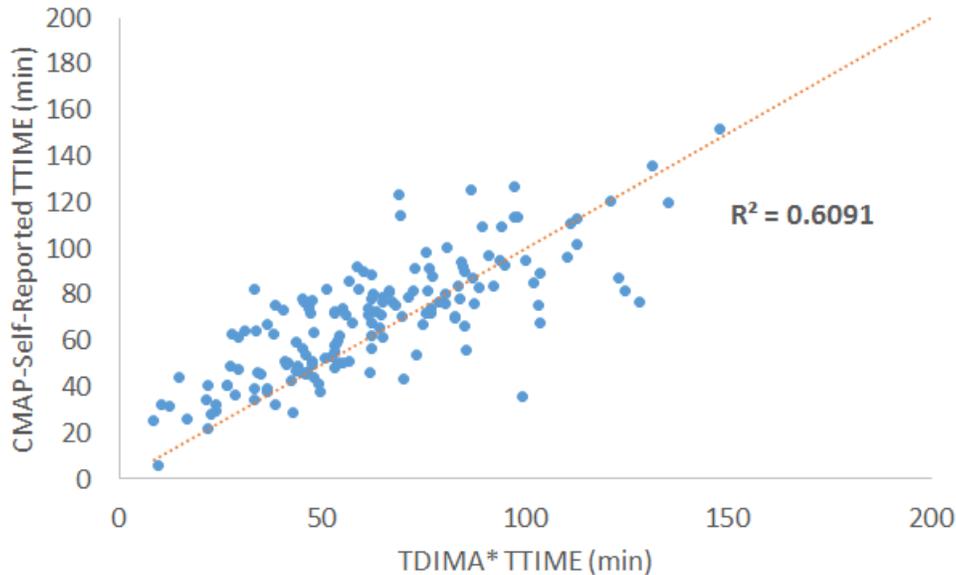


Figure III.6-3 - Time-Dependent Intermodal A* Routing Results vs. CMAP Self-reported Travel Times

Conclusions

The POLARIS model has been significantly enhanced to simulate the impact of various traveler behaviors under different future mobility scenarios. Key improvements to the vehicle choice, activity planning, and route choice models have been implemented and tested for various policy scenarios. The updated model was used to explore potential impacts of telecommuting policies, and demonstrated minor energy reduction with increased telecommuting.

Key Publications

1. Shabanpour, R., N. Golshani, J. Auld, O. Verbas, and A. Mohammadian. "Analyzing Telecommuting Behavior and Impacts on Regional Travel Demand through Simulation." Presented at IEEE – Models and Technologies for Intelligent Transportation Systems, Naples, Italy, June 26–28, 2017.
2. Verbas, O., J. Auld, H. Ley, R. Weimer, and S. Driscoll. "A Time-Dependent Intermodal A* Algorithm: Methodology and Implementation on a Large-Scale Network." Accepted for publication in Transportation Research Record, 2018 (forthcoming).
3. Golshani, N., R. Shabanpour, J. Auld, and A. Mohammadian. "Activity Start Time and Duration: Incorporating Regret Theory into Joint Discrete-Continuous Models." Accepted for presentation at the 97th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2018.

IV. Smart Mobility – Multi-Modal Transport

IV.1 Develop Smart Vehicle Energy Technology (SVET) Passenger Fleet Model [Task 1.1]

Tim LaClair, Principal Investigator

Oak Ridge National Laboratory (ORNL)
2360 Cherahala Boulevard
Knoxville, TN 37932-6472
Phone: (865) 946-1305
E-mail: laclairtj@ornl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$175,000

End Date: September 30, 2017
DOE share: \$175,000

Non-DOE share: \$0

Project Introduction

As part of the U.S. Department of Energy’s (DOE) Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Initiative, the Oak Ridge National Laboratory (ORNL) led a study to develop web-based tools that will enable vehicle fleet operators to quantify the energy savings achievable by implementing advanced transportation technologies. By developing a profile of a fleet’s existing vehicle inventory and providing data about how and where the vehicles are driven, fuel consumption will be calculated for the entire fleet, and users can perform “what if” scenarios to evaluate the energy savings that can be realized when replacing existing vehicles and implementing new technologies. The Smart Vehicle Energy Technology (SVET) model for passenger vehicles will account for vehicle usage by evaluating speeds and road grades within the region where the vehicles are operated so that the energy use is calculated based on driving conditions that are representative of those experienced by the fleet. The SVET tool will assist those responsible for fleet procurement and operations to select alternative fuel/energy efficient vehicles and technologies and to quantify the energy savings provided by these vehicle/technology selections. Virtually any advanced vehicle technology such as new powertrain systems (new engine designs, electric vehicles, and hybrids), alternative fuel options (CNG, ethanol, etc.), and connected and automated vehicle (CAV) applications (signal eco-approach and departure (EAD) and Eco-Cruise), can be evaluated with the tool. The tool was designed so that users are not required to have any knowledge of vehicle performance analysis and can easily evaluate advanced vehicle technology options to estimate the energy benefits under the use conditions of the user’s fleet.

The intent is that the tools will quickly guide users through the process of creating their fleet profile of vehicles, defining the vehicle usage, with varying levels of detail to be provided within the model, depending on the intended purpose of the evaluation and availability of data. For users that are more familiar with their fleet’s drive cycles, alternative methods will also be available to describe usage for each vehicle included in the inventory. In this way, fleet managers will be able to generate appropriate inputs at a level consistent with their organization’s availability of information and needs.

Objectives

The purpose of this effort is the development of a science based, well-documented and ready to use Smart Vehicle Energy Technology (SVET) application to assist fleets in the selection of alternative fuel/more energy efficient vehicles, including existing and anticipated electric vehicle options. The project goals were oriented specifically at conducting energy savings evaluations for entire vehicle fleets to assist fleet procurement and operations personnel in tracking and managing energy use reductions. Public agencies and private corporations operating vehicle fleets will benefit from the availability of the SVET model as it will facilitate their ability to compare the performance of alternative vehicle technologies based on energy/fuel efficiency, operating and maintenance costs. As it enables agencies and organizations to assess the benefits of electric vehicles as candidates for their fleets, it will accelerate the deployment of EV Everywhere (EVE). SVET was developed to calculate energy savings based on the difference in energy consumption between an existing fleet and future scenarios for deployment of advanced vehicle technologies. The work plan included a review of current scientific research on energy saving vehicle technologies, particularly the research underway or completed by the national laboratories. The resulting model will estimate energy savings and allow energy comparisons between the current fleet and scenarios for future deployment of advanced vehicle technologies based on the most up to date science.

Approach

SVET was developed as a web-based tool, with the goal of providing easy-to-use and accurate, science-based estimates of the energy savings that a passenger vehicle fleet can achieve when employing advanced vehicle technologies. The tool is intended for users that do not necessarily have any expertise in vehicle analysis, so ease of use was a primary consideration in the tool's development. Nevertheless, SVET allows evaluations of a broad range of technologies based on a fundamental energy-based evaluation of vehicle operation. Table IV.1-1 shows a list of vehicle technology options that users can select from the SVET user interface.

Table IV.1-1 - List of Vehicle Technology Options Available in SVET

Vehicle types:
Light duty cars and trucks
Propulsion systems:
Conventional internal combustion engine (gasoline, diesel, natural gas or hydrogen)
Gasoline direct injection engines
Turbocharged engines
HEVs (hybrid electric vehicles)
PHEVs (plug-in hybrid electric vehicles)
Mild hybrid vehicles
BEVs (Battery electric vehicles)
Fuel cell vehicles
CAV technologies:
Traffic signal eco approach and departure
Connected Eco-Driving

Other fuel efficiency technologies:
Advanced aerodynamics (active grill shutters, under body drag reduction devices, etc.)
Advanced transmissions: 7- to 11-speed
Vehicle Lightweighting (carbon fiber body panels, low mass glider, compacted graphite iron (CGI) block)

The basic vehicle and powertrain parameters that must be specified prior to running the model include the powertrain type, engine and/or motor size, transmission gear ratio data, vehicle mass and parameters for the road load characteristics of the vehicle. For production passenger vehicles sold in the United States, the U.S. Environmental Protection Agency (EPA) provides data on fuel economy and publishes its annual “test car list,” which includes fuel economy data along with other information about each vehicle. Much of the data needed for the SVET model is contained within the EPA test car list, so this can be used as a means to directly select vehicles and load much of the required model data. The EPA test car list is stored within the SVET database, and the user can make vehicle selections based on the vehicle year, make and model. SVET then loads the parameters for the selected model from the test car list, although the user is able to manually edit any of the parameter data as desired. (Alternatively, the user can enter tire rolling resistance, aerodynamic drag coefficient and vehicle frontal area instead of specifying the “a, b, c coefficients” that are normally used to provide the road load characterization for passenger vehicles.) A screenshot of the vehicle selection window is presented in Figure IV.1-1.

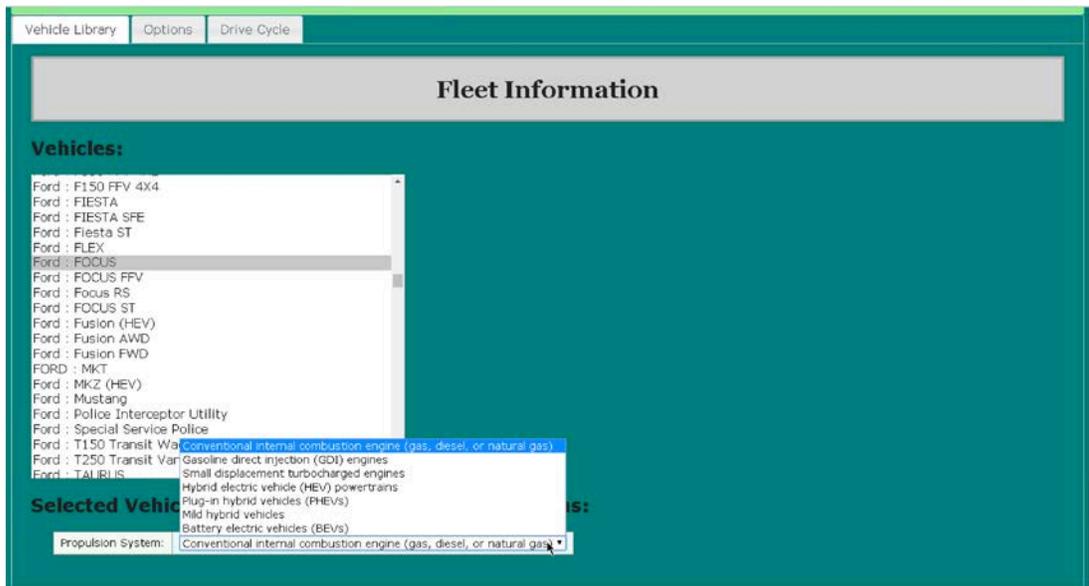


Figure IV.1-1 - Screenshot of the vehicle selection page in SVET.

When technology options that are not part of the selected vehicle make and model are to be evaluated, a base vehicle can be selected as a starting point and the other technology selections can be added to define the final vehicle characterization including the desired technology options. SVET will make modifications to model parameters as appropriate to provide a vehicle characterization that is relevant for the user-selected technology options, enabling “what-if” evaluations of new technologies even when specific vehicle models have not identified. Single vehicle evaluations and comparisons can be performed with SVET, although the tool was developed with broader fleet evaluations in mind. To develop a fleet profile in the tool, the user specifies each

vehicle type comprising the fleet by following this same vehicle selection approach, and can enter as many vehicles as desired to specify the full fleet inventory.

Usage data for all vehicles must also be specified. Each vehicle in the fleet will have a usage associated with it for the model calculation, but the same usage may be used for multiple vehicles if they experience similar overall driving conditions. The usage specification is defined by drive cycles, which consist of speed vs. time data characterizing the typical driving conditions experienced. Elevation data may also be included in a drive cycle if there are significant elevation changes in the region where the vehicles are operated. The drive cycle data can either be based on direct measurements of vehicle speeds and road grades from vehicles in the fleet, or the user may select from standard drive cycles that are representative of the operations in the fleet. More complex usage scenarios can also be defined based on a weighted fraction of driving among multiple drive cycles. For example, if a vehicle is driven approximately 20% of its annual miles in highway conditions, 30% in congested traffic conditions and 50% in non-congested urban/sub-urban conditions, then three drive cycles that represent the highway, congested city, and non-congested urban driving can be used to represent the overall vehicle usage, with the 20%/30%/50% weighting applied to the three drive cycles, respectively. This approach allows a limited set of drive cycles to represent a fairly diverse range of driving conditions, and although it may not be as precise as having measured data for individual vehicles, it provides a means to generate a very reasonable usage specification that users can easily understand to estimate the blend of driving conditions that represents the usage with reasonable accuracy. After defining a set of usage specifications that are appropriate for each vehicle in the fleet, the user links the vehicles in the fleet profile to corresponding usage cases and enters annual mileage data, as shown in Figure IV.1-2. Entering the fleet profile and the usage specifications for all vehicles in the fleet represents all of the inputs required to run the fleet analysis. The process described above will be repeated to define the current (baseline) fleet configuration and any alternative fleet configurations with advanced technology options that the user wishes to evaluate and compare.

Smart Vehicle Energy Tool (SVET)

Vehicle Library | Options | Drive Cycle

Baseline fleet:

Vehicle	Usage	Avg Annual Miles Travelled	# of Vehicles
2016 Ford Focus	Knoxville City	10,000	2
2016 Ram 1500 4WD, 8 cyl, 5.7L	70% City / 30% Hwy	15,000	1
2015 Honda Accord, 4 cyl, 2.4L	70% City / 30% Hwy	18,000	1

Run Model | Load Parameters | Save Parameters

Thank you for using SVET.

[Main Menu](#)

Figure IV.1-2 - Screenshot of a fleet profile specification in SVET

Determining the energy savings for the fleet when implementing selected vehicle technology options is done by directly calculating the difference in energy consumption for all vehicles in the fleet between an initial and a final fleet configuration. The energy consumption calculations are based on a simplified vehicle powertrain model, corresponding to the selected powertrain type and using the usage specification to characterize the driving characteristics of each vehicle. The tractive power required to propel the vehicle is calculated at each point in time using the specification data and the drive cycle inputs, and component efficiencies are then used

to determine the energy use from the primary energy source(s) (fuel and/or electrical energy) corresponding to each vehicle’s powertrain. In this manner, the model accounts for the energy flows/conversions/losses for the fuel, the powertrain components and the overall vehicle using a physics-based evaluation.

A literature review was conducted at the beginning of the project to identify models and approaches used in other tools, and the methodology employed in SVET follows commonly accepted methods for vehicle powertrain modeling [1-5]. We note that the same underlying vehicle model is used both for SVET and for the Freight Fleet Level Energy Estimation Tool (FFLEET) developed in the project “Inter-City Freight Movement Optimization Model and Data,” which is also described in this FY2017 Annual Progress Report. Fundamental differences in user needs, relevant technologies and the basic use cases between the passenger and freight-hauling vehicles resulted in the development of separate tools, but the methodology used for the vehicle model remains very similar for both SVET and FFLEET.

This drive cycle-based powertrain modeling approach allows a broad range of technologies to be evaluated, and the results of the analysis are specific to the selected vehicle configuration and the usage specification so that the user is able to quantify the benefits that can be achieved for a particular technology implementation for the specific type of driving that is done and for the types of vehicles that operate within the fleet. The parameters that characterize the vehicle and powertrain components are modified in the model to account for technologies that function by directly changing the vehicle or powertrain characteristics, while technologies that impact the usage (speeds and accelerations) can be accounted for by modifying/filtering the drive cycle data in a manner representative of the deployed technology. This approach of modifying the drive cycles allows a simple evaluation of various connected and automated vehicle (CAV) applications to be conducted using the same modeling approach as is used for the powertrain technology evaluations and they can be done simultaneously with other technologies so that interactions between the various technologies can be evaluated in a consistent manner.

Results

The SVET tool was developed as several software modules with specific functions. The web-based user interface (front end) provides prompts to the user to select and specify vehicle and fleet parameters, upload files, and return/display output from the model. The server-side (back end) includes a database to store user-entered data and other data used in the model creation, and manages interactions between the front-end and the vehicle model. The vehicle model itself performs all calculations necessary to determine the energy consumption for each vehicle evaluated. The front-end was developed using HTML, Javascript, and JQuery languages; the back-end using Python, Json, and SQL languages; and the vehicle model was written in Python. Figure IV.1-3 shows the relationship between the software modules and the database architecture.

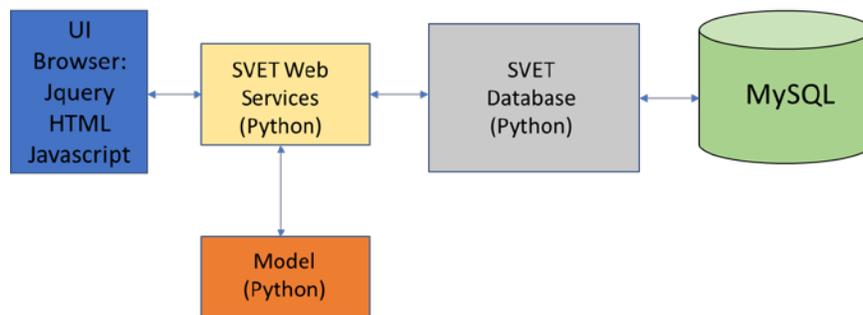


Figure IV.1-3 - Software modules for the SVET web-based tool

The primary output from a SVET simulation is the fuel consumption result. When a fleet evaluation is selected (i.e., multiple vehicles), output data will be provided to the user in a table summarizing the model results for all vehicles, as shown in Figure IV.1-4, and the expected annual energy savings due to the selected vehicle

technology options in the alternative fleet scenario are calculated. In addition to the fuel summary data, the user may choose to view graphs showing individual vehicle results. Several graphs of modeling results from the vehicle analysis are available for display depending on the options selected. Figure IV.1-4 shows the drive cycle (vehicle speed and elevation) along with the fuel consumption results as a function of time. Similar graphs are available with key performance data for any vehicle simulation performed.

Vehicle	Usage	Avg Annual Miles Travelled	# of Vehicles	Average mi/GGE	Total Energy Consumption (GGE)
2017 Ford Fusion HEV	Knoxville City	10,000	2	41.7	479.6
2017 Ford 150, 6 cyl, 2.7L (GDI Turbo)	70% City / 30% Hwy	15,000	1	18.6	806.5
2017 Honda Accord, 4 cyl, 2.4L (Eco Cruise/EAD)	70% City / 30% Hwy	18,000	1	31.5	571.4
total energy consumption (GGE):					1857.5

Figure IV.1-4 - Energy consumption results estimated by SVET for a fleet configuration

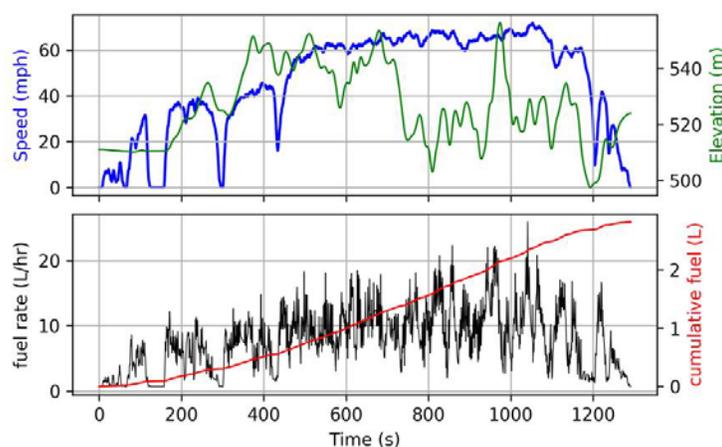


Figure IV.1-5 - Detailed vehicle model results can be displayed for the individual vehicle simulations

Conclusions

The SVET model, a web-based software tool aimed at estimating the energy savings achievable in passenger vehicle fleets when implementing advanced vehicle technologies, was developed by ORNL in FY 2017. SVET allows users to enter a profile of a fleet's existing vehicle inventory and provide vehicle usage data using a simple but flexible approach, and the tool will calculate fuel consumption data for the entire fleet. Starting with the initial vehicle inventory profile, the user can perform "what if" scenarios to evaluate the energy savings that can be realized when replacing existing vehicles and implementing new technologies. This tool was designed for ease of use and will assist those responsible for fleet procurement and operations to understand the benefits that their fleet can achieve with alternative fuel/energy efficient vehicles and technologies, including various connected and automated vehicle (CAV) technologies.

Key Publications

1. T. LaClair, D. Davidson, "Passenger and Freight Fleet Energy Saving Models for SMART Mobility" (literature review of vehicle powertrain models and a detailed description of objectives for the FFLEET and SVET models), submitted with the FY 2017 Q1 Quarterly Project Report to DOE, Jan. 2017.
2. T. LaClair, "Functional Specification for the FFLEET Web-Based Tool," submitted with the FY 2017 Q1 Quarterly Project Report to DOE, Jan. 2017.

References

1. Philips, P., "Analytic Engine and Transmission Models for Vehicle Fuel Consumption Estimation," *SAE Int. J. Fuels Lubr.* Vol. 8(2):2015.
2. E.K. Nam and R. Giannelli, *Fuel Consumption Modeling of Conventional and Advanced Technology Vehicles in the Physical Emission Rate Estimator (PERE)*, Report Number EPA420-P-05-001, Office of Transportation and Air Quality, U.S. Environmental Protection Agency, 2005.
3. F. An and M. Ross, "A Model of Fuel Economy and Driving Patterns," SAE Technical Paper 930328, 1993.
4. Brooker, J. Gonder, L. Wang, E. Wood, S. Lopp, L. Ramroth "FASTSim: A Model to Estimate Vehicle Efficiency, Cost and Performance," SAE Paper 2015-01-0973, 2015.
5. K. Ahn, H.A. Rakha, K. Moran, "A simple fuel consumption model based on instantaneous vehicle power," Proceedings of the Transportation Research Board 89th Annual Meeting, Washington, D.C. pp.10–14, January 2010.

IV.2 Modeling and Analysis of the Effect of Multi-Modal Intra-City Passenger Travel on Mass Transit Systems [Task 1.2]

Tom Wenzel, Project Manager, Principal Investigator

Organization: Lawrence Berkeley National Laboratory
 Address: 1 Cyclotron Road
 Berkeley, CA 94720
 Phone: (510) 486-4000;
 E-mail: colin.sheppard@lbl.gov

David Anderson, Program Manager

U.S. Department of Energy
 Phone: (202) 287-5688
 E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2017

Total Project Cost: \$450,000

DOE share: \$450,000

Non-DOE share: \$0

Project Introduction

The SMART Mobility consortium has set out to answer a set of far-reaching questions about the future of mobility systems and their impact on transportation sector energy consumption. This highly ambitious effort is also founded on the idea that a systems modeling approach is critical to analyzing the inter-dependent impacts of changes to transportation behaviors and technologies.

One key example of the inter-related impact of behaviors, technologies, and system level outcomes is induced demand. As technology enables new and existing transportation services to serve demand more efficiently in terms of energy, time, and cost, then more people will use those services. As demand for new and improved services increase, the gains in efficiency will be marginally eroded until a new system equilibrium is established that accounts for interactions between traveler preferences and the capacity of the system.

Traditional dynamic traffic assignment simulation models (DTA) are designed to facilitate the analysis of hypothetical changes to the transportation system. This typically means adding new capacity to the road network (e.g., by adding lanes). These approaches tend to use static representations of demand (origin/destination matrices) that ignore the continuity of travelers over the course of a day (i.e., they represent unconnected trips instead of individual activity patterns) or the details of system supply such as the movements of transit vehicles, taxis or ride hailing vehicles.

Traditional DTA's are therefore ill-equipped to enable systems analysis that can capture many of the newly complicating features of the emerging transportation sector. For example, modern discrete choice analyses of traveler preferences now capture nuanced heterogeneity in traveler preferences, which are difficult to holistically embed in a traditional DTA model. Other traveler behaviors such as car-pooling and multi-modal trip planning via transit cannot be captured through DTA other than by making broad, high-level assumptions about their ultimate effect on trip distributions. Finally, as transportation network companies (TNCs) innovate in providing mobility services in a multitude of new ways, a simulation platform that doesn't represent the detailed operations of these services will be incapable of projecting their benefits and impacts before they've been fully integrated into the market.

In this task, we have embarked on a much more comprehensive approach to analyze the transportation system. We are employing agent-based modeling to simulate the behaviors of individual travelers as they engage with the system, allowing us to represent traveler heterogeneity and the detailed operations of mobility services,

including transit as well as TNCs. Our initial and primary focus is on mode choice, as this can have dramatic impacts on the energy footprint of the transportation system.

Objectives

The objectives of Task 1.2 are as follows:

- Enhance and extend BEAM (the Framework for Behavior, Energy, Autonomy, and Mobility) to enable scalable simulations of the increasingly dynamic and inter-dependent transportation system.
- Apply BEAM to one or more urban regions.
- Conduct model calibration to ensure BEAM makes robust predictions of system level outcomes such as traffic patterns, modal splits, and TNC operations.
- Use the calibrated model to conduct analyses that assess the impact of emerging mobility services or other system changes on modal distribution and system energy consumption; e.g., to what extent can TNCs complement versus compete with transit, and how does this change with the pricing of mobility services from TNCs?

Approach

Our approach involves four main sub-tasks:

1. **Enhance and extend BEAM (the Framework for Behavior, Energy, Autonomy, and Mobility) to enable scalable simulations of the increasingly dynamic and inter-dependent transportation system.**

The BEAM Framework acts as a plug-in to the MATSim model. MATSim features a modular simulation engine that employs an iterative scheme and co-evolutionary optimization to achieve user equilibrium in the transportation system. In other words, the simulation of a typical weekday is repeatedly executed and the individual agents are given the opportunity to modify their travel plan for the day after each round. The basis for modifying their plan and selecting from a learned history of old plans depends on the scoring step, which evaluates a utility function. In its most basic form, the utility function yields positive utility (with decreasing marginal returns) for engaging in one’s activities and negative utility for traveling. But the utility function is extensible and can be modified to include any new events that are relevant to the traveler’s experience; for example, range anxiety experienced by

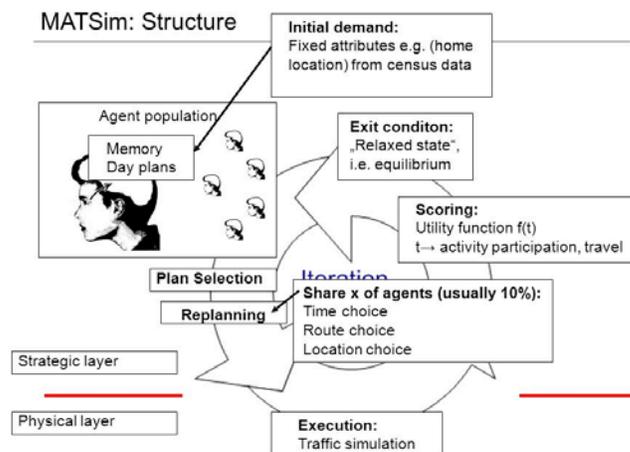


Figure IV.2-1 - MATSim iterative structure (Horni, 2017).

the driver of a battery electric vehicle can be implemented as additional disutility in the function.

BEAM extends the scoring and replanning capabilities of MATSim to allow travelers to exhibit adaptive behaviors within the simulation day, rather than between days. This focus on the dynamic interactions between agents and the mobility system during the day enables BEAM to capture the detailed operations of mobility services like transit and TNCs while simultaneously allowing these operations to influence traveler behavior through the mode choice mechanism.

BEAM is also designed for scalability. Though the MATSim framework is highly extensible, only a limited features set (mostly traffic flow) has been optimized for computing at massive scale (full sample of cities with millions of agents). BEAM has been designed from the ground-up to enable large scale simulations on distributed processors through use of the actor model of computation.

The actor model (Hewitt et al, 1973) is a formalism for concurrent programming which fully encapsulates units of computation as “actors” and prescribes a system of communication between the actors (messaging) which simplifies reasoning about control flow and memory access within actors

BEAM Framework

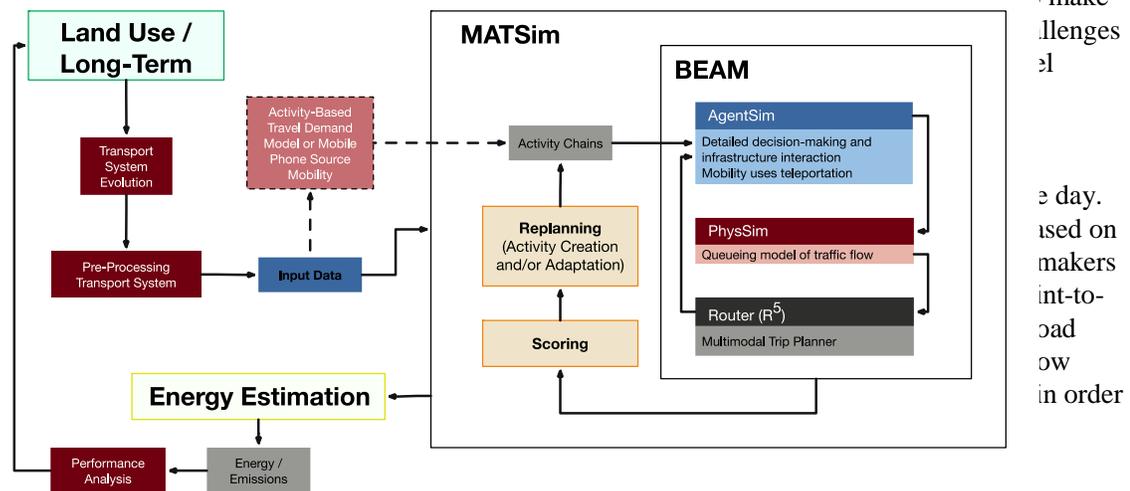


Figure IV.2-2 - Master plan for the BEAM Framework. In FY 2017, the focus has been on development and integration of the BEAM modules within MATSim.

Within the AgentSim, travelers execute a mode choice model which evaluates the utility of modal alternatives and then samples from the resulting distribution. In the preliminary implementation of BEAM, several mode choice models have been developed and used for various purposes. The results below were created using a simple multinomial logit model which has four alternatives: DRIVE, TRANSIT, WALK, and RIDE HAIL. Each linear utility function considers time and cost, with parameters chosen so the ratio is equivalent to the value of time assumed for the model run (e.g., our base scenario in the results below assumes \$18/hr). The transit alternative also includes the number of transfers as an independent variable in the utility function. When travelers are faced with multiple alternatives that qualify as one of the four outlined above, the best representative trip itinerary is used to evaluate the overall utility function for that mode and is used if that mode is chosen.

Finally, the outcome of the simulated day is characterized in terms of vehicle trajectories, allowing for post-processing to quantify the energy consumption of the system across space, time, mode, or other dimension of

interest. Energy consumption estimates are currently based on fleet average EPA combined city/highway fuel economy certification ratings. In FY 2018 we have proposed including more detailed models of energy consumption in partnership with NREL using MOVES.

2. Apply BEAM to one or more urban regions, beginning with the San Francisco Bay Area.

Based on previous work conducted by the Smart Cities Research Center at UC Berkeley and the Metropolitan Transportation Commission (MTC), we have focused our initial application development on the San Francisco Bay Area where we have a ready source of activity plans from the MTC Activity-Based Travel Demand Model (MTC, 2012). We sample from these 2.5M activity chains to any desired subset and combine the plans' data with U.S. Census data to create synthetic populations with representative spatial demographics, including characteristics such as household size, number of cars per household, and income.

We use the R5 network loading capability to parse data from Open Street Map and as well as transit feed data from the 28 local transit agencies in the Bay Area to create the transportation network representation used for routing. Finally, we collected a database of transit fleet data which we use to assign transit vehicle types (e.g., diesel versus electrified buses) to the trips in the transit feed data.

3. Conduct model calibration to ensure BEAM makes robust predictions of system level outcomes such as traffic patterns, modal splits, and TNC operations.

This work will primarily happen in FY 2018, but we have already conducted preliminary calibration of the multinomial logit choice model to match aggregate observed modal splits in the Bay Area. Based on data available from the MTC, we have adjusted the intercepts of the utility functions of the four alternatives in the model described above to create the results presented below. In the coming months, we will expand our calibration work to cover the more advanced latent class choice model which has the advantage of yielding modality styles as an output of the simulation. See our Annual Deliverable for a more detailed explanation of this approach.

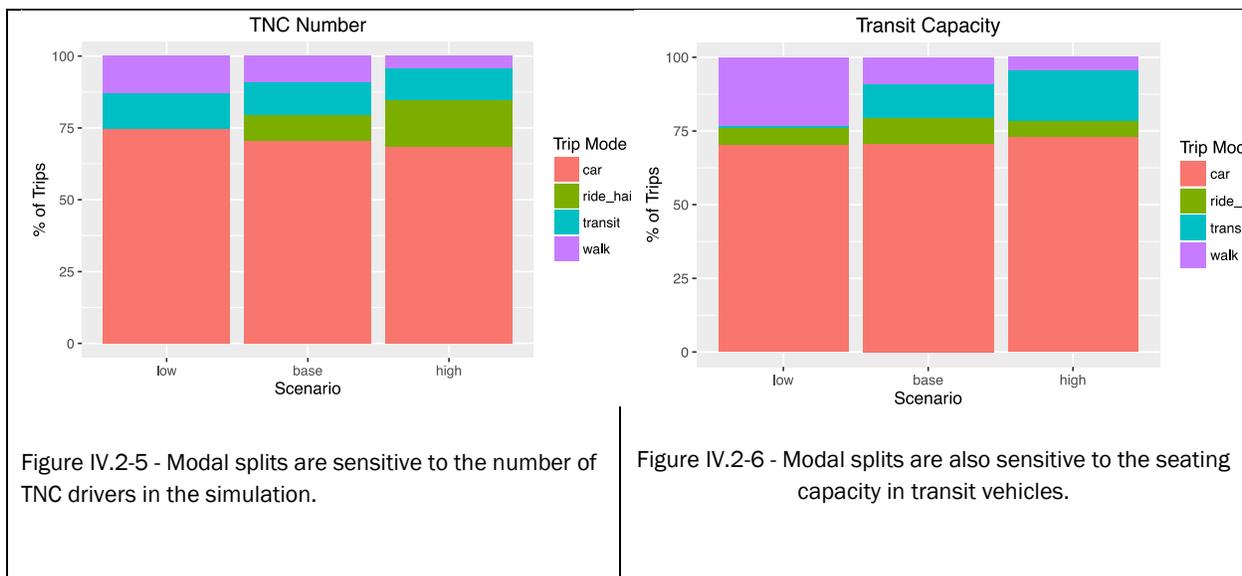
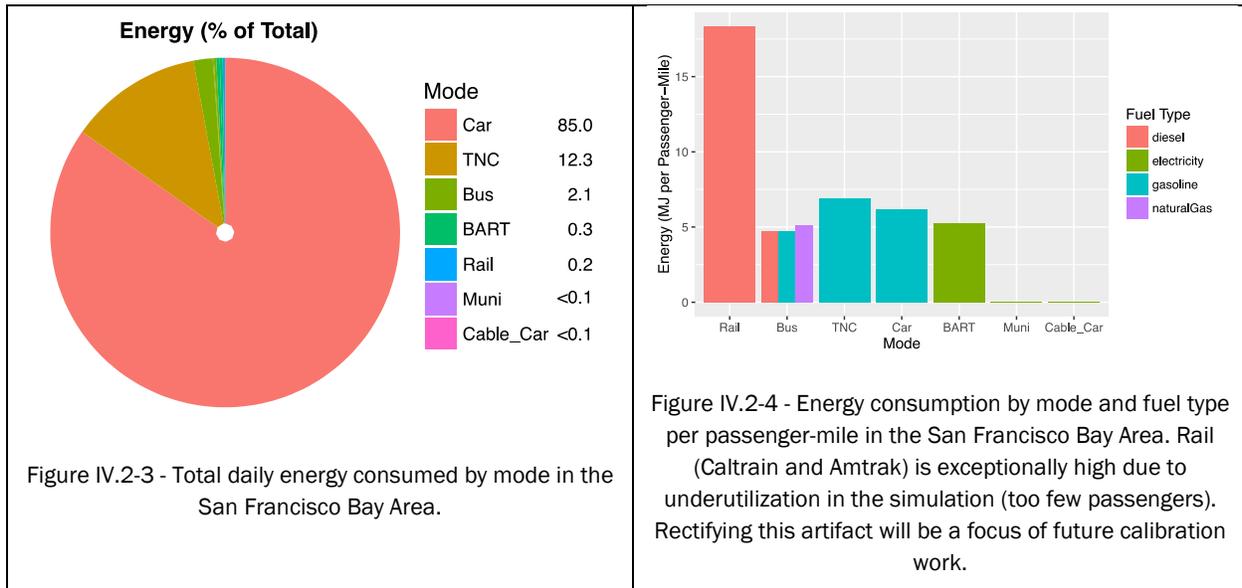
4. Use the calibrated model to conduct normative analyses that assess the potential to leverage knowledge about human behavior to incentivize beneficial system outcomes.

This work will occur in FY 2018-FY 2019. An early task in FY 2018 is to clearly define the range of analyses that will be conducted with the calibrated BEAM model. For example, to what extent can cross-subsidies or other incentive schemes induce shifts in travel among modes and reduce the energy use of the system?

Results

The results presented below represent preliminary examples of the kinds of outputs and analyses that BEAM is capable of producing for the San Francisco Bay Area. Though we use a choice model that exhibits reasonable sensitivities to changes in modal alternatives (i.e., it is sensitive to trip time and cost), the calibration was preliminary and therefore the model has yet to produce robust agreement with observe data across all dimensions of interest. Nevertheless, these results are illustrative of the benefits of agent-based simulation

modeling which can be observed with complete omniscience and therefore the system can be analyzed in a multitude of ways.



Conclusions

In FY 2017, we have successfully enhanced the BEAM/MATSim simulation platform to achieve scalable, dynamic simulation capabilities that include all modes of travel and we have applied the model to the San Francisco Bay Area.

Key Publications

We have presented our ongoing work in the following venues:

- SMART Mobility Modeling and Simulation Tools Workshop. Oak Ridge National Laboratory, November, 2016.
- SMART Mobility / Smart City Challenge Coordination Workshop. Columbus, Ohio. December, 2016.
- U.S. DOE Annual Merit Review. Washington, DC. June, 2017.
- ITS World Congress. Montreal, QC. October, 2017.

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IV.3 Enhance Existing Models to Estimate Impact from Modal Shifts in Intra-city Passenger Travel [Task 1.3]

Ram Vijayagopal, Omer Verbas (Principal Investigators)

Argonne National Laboratory
9700 S. Cass Avenue, Bldg. 362
Argonne, IL 60439
Phone: (630) 252-2849
E-mail: ram@anl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$170,000

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DOE share: \$170,000

Non-DOE share: \$0

Project Introduction

The multi-modal pillar of SMART aims to quantify the energy requirements of moving people and freight. Argonne's role is to use Polaris and Autonomie to estimate transit related energy consumption. The existing modeling capability available in Autonomie was sufficient to analyze all types of light-duty vehicles, and this capability was enhanced during this project to include transit buses of various types. An accurate model of vehicle powertrains and component technologies is necessary to properly estimate the energy impact new shared mobility will have on intra-city passenger travel.

Objectives

- Simulate multiple vehicle configurations, platforms, and time frames to quantify their benefits.
- Estimate how various trends in multimodal passenger travel will affect overall energy use within an entire metro area.
- In fiscal year (FY) 2017, the focus was on developing accurate energy models of transit vehicles.
- Integration into large-scale transportation system simulator (Polaris) will occur later in the project.

As part of achieving these objectives, we performed detailed literature review and data analysis related to current transit bus performance and technology. The data collected on multiple buses in the U.S. and Canadian markets helped in identifying one representative transit bus model. We developed multiple powertrain options, including conventional, ISG, high-efficiency vehicle (HEV), plug-in hybrid electric vehicle (PHEV), battery electric vehicle (BEV), and FCEV. The baseline vehicle model was compared against test data from the Federal Transit Administration. The electrified vehicle variants were sized to match four important performance requirements of the baseline conventional vehicle.

Approach

Several popular bus models were examined to develop a representative candidate for the transit bus. We selected the Nova LFS since most vehicles in this class are similar and many cities have this model in their fleet. The Chicago transit authority can also provide data for similar buses, which form the backbone of their fleet. The Nova LFS is a 40-foot bus with a 9-liter engine and a 6-speed automatic transmission. Table IV.3-1 shows the performance data for this vehicle. Vehicle performance is not typically advertised for heavy-duty vehicles, so these numbers are based on simulation results.

Table IV.3-1 - Technical and Performance Specifications for the Baseline Transit Bus

Parameters	Class 8 Transit Bus
Engine (kW)	243
Test Mass (lb.)	36,439
Cargo Mass (lb.)	4,042
Daily Distance (miles)	150
Cruise Speed (mph)	60
6% Grade Speed (mph)	36
0-30mph (s)	13
0-60mph (s)	50

To model the future vehicles that could replace these buses, our team developed models for hybrid and electric variants of the bus. Appropriate component sizing plays an important role in determining the impact of the technology. In case of commercial vehicles, it is critical that the vehicle performance not be sacrificed in the quest for better fuel economy. The component sizing process for each powertrain ensures that the proposed vehicle can either match or better the performance of the baseline vehicle.

We used the EPA’s regulatory cycles to compare fuel consumption benefits. The component sizing for hybrids looked at optimizing the fuel savings in the ARB transient cycle. When it comes to setting energy storage requirements for driving range, we assumed the worst-case scenario. VIUS data shows that similar buses require about a 150-mile range to meet 90% of the driving requirements. Highway driving at 65 mph is the most energy-consuming cycle among the three regulatory ones. If we size the vehicle to drive 150 miles in that cycle, it would be able to drive longer distances in almost all real-world driving scenarios.

Sizing Approach

In general, the components in the powertrain are sized to meet transient power requirements (acceleration) and continuous power requirements (grade and cruise) as shown in Table IV.3-2. The grade test used in the simulation is a simplified version of the Davis Dam test, where the objective is to measure the maximum sustainable speed toward the end of an 11-mile drive at a steady 6% grade. Hybrid components can assist when transient power is necessary, but they are not useful in meeting the continuous power requirements. The maximum power output of motors varies gradually because the component is de-rated as its operating temperature goes up. The thermally sustainable power output usually varies slightly based on the operating speed. The cargo mass during the test is arbitrarily set at 50% of the expected load. All variants will use the same cargo load for the test, but the each test weight will vary based on components used in the powertrain design.

Table IV.3-2 - Sizing Criteria for Powertrain Components

Parameters	Engine Power	Motor Power	Battery
Conventional	Acceleration grade and cruising		
ISG	Same engine power as the conventional baseline	Alternator and starter in baseline	Power availability at 40% SOC. Ability to meet auxiliary loads for at least 1 minute
HEV	Acceleration grade and cruising	Minimizing fuel consumption on ARB transient cycle	Minimizing fuel consumption on ARB transient cycle
BEV		Acceleration grade and cruising	Achieve the target range on EPA 65 cycle

Results

Performance

Acceleration times to 30 and 60 mph are two critical performance criteria. Figure IV.3-1 - Hybrid Variants Provide Better Performance than Baseline Vehicle shows that all hybrid variants provide better performance than a conventional vehicle. All variants can sustain speeds of 36 mph or higher at a 6% grade. We set the cruise speed requirement at a minimum of 60 mph, and all vehicles satisfy this criterion.

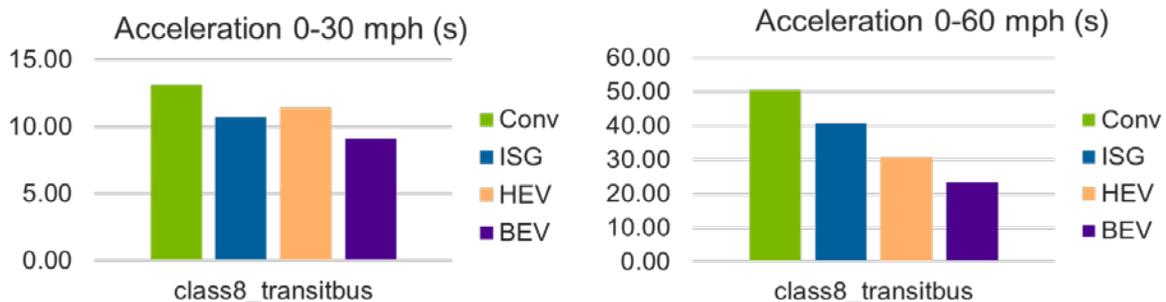


Figure IV.3-1 - Hybrid Variants Provide Better Performance than Baseline Vehicle

Fuel Savings

In the stop-and-go traffic depicted by the ARB transient cycle, ISGs and HEVs provide fuel consumption reductions of 18% and 43%, respectively (Figure IV.3-2).

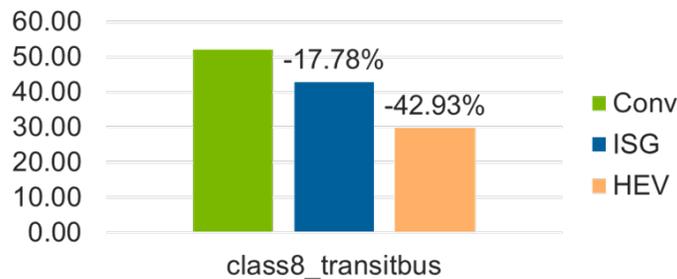


Figure IV.3-2 - Fuel Consumption Reduction in ARB Transient Cycle

EREVs, BEVs, and FCEVs directly displace diesel consumption, and it is clear that their savings depend directly on the size of their battery or onboard hydrogen tank. Efforts are underway to include the initial cost and ownership cost in the sizing analysis.

As of now, the PHEVs are sized for a range of 100 miles, and BEVs and FCEVs are expected to run the full range of 150 miles using their respective onboard energy storages.

Conclusions

Transit bus models were built for multiple powertrains, including conventional, ISG, HEV, PHEV, BEV, and FCEV. All of the advanced variants match or exceed the performance and cargo capability of the baseline vehicle. We shared these results with industry partners to obtain feedback on the approach and sizing methodology. Several OEMs agreed with the performance characteristics, but they also provided valuable suggestions regarding additional performance sizing criteria. We will continue to gather both public and proprietary information regarding costs.

Key Publications

1. “Fuel consumption and performance benefits of electrified powertrains for medium and heavy duty vehicles” accepted at SAE World Congress 2018.

IV.4 Impact of Shared Mobility Use on Public Transit Services and Urban Form [Task 1.4]

Susan Shaheen, Principal Investigator

UC Berkeley, LBNL
408 McLaughlin Hall
Berkeley, CA 97010
Phone: (510) 642-9168
E-mail: sshaheen@berkeley.edu

Victor Walker, Principal Investigator

Idaho National Laboratory
2525 Fremont Ave
Idaho Falls, ID 83402
Phone: (208) 526-8959
E-mail: victor.walker@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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Non-DOE share: \$0

Project Introduction

Shared mobility systems, such as car sharing, have facilitated automotive access on a temporary basis, which allows people to gain automotive mobility without the need to own vehicle. Such a transformation facilitates greater multi-modalism, which ultimately reduces the energy use and emissions derived from transportation activity. A number of studies have evaluated the impacts of car sharing systems on vehicle holdings, vehicle acquisitions, driving, and overall modal shift. But much more can be learned through a deeper inspection of existing survey and activity data that allow us to identify how shared mobility systems can best support multi-modal behavior, and where such systems are most effective in facilitating transitions to reduced personal vehicle ownership and multi-modal travel behavior.

In this project, researchers are using survey and vehicle activity data collected through car2go, the largest car sharing operator in the world, to study activity patterns and mode shift dynamics that are caused by shared mobility systems. Car2go delivers what is called one-way free-floating car sharing in that it provides one-way car sharing within a large urban zone. Members can pick up a vehicle parked anywhere in the zone and drop it off anywhere else in the zone to close their session. They pay only for the time that they use the vehicle. Car2go is the largest one-way car sharing operator in the world, operating in about 30 cities.

Researchers affiliated with UC Berkeley and LBNL have conducted research evaluating the high-level impacts of car2go on vehicle holdings, VMT, and modal shift. Leveraging this early work and associated data resources, this project is advancing an in-depth understanding of urban mobility patterns and modal shift within the context of the urban and infrastructure environment. One of the key innovations of this project is to understand the relationship between land-use, density, as well as public transit operations and infrastructure to impacts from one-way shared mobility systems. Developing this understanding requires a solid foundation of data descriptive of the public transit system and operations.

The research team at INL is further expanding the integration of public transit operational and infrastructure data into the analysis of shared mobility system impacts. Researchers at INL are building a database of transit operational attributes to establish inputs into the modeling efforts of the broader project. The database assembled by the INL effort will provide the foundation for a broader DOE understanding of public transportation operations as well as potential further exploration of public transit energy consumption across and within systems. The analysis of shared mobility impacts and its relationship to public transit and land-use will inform policy and understanding of potential impacts of such systems within broader regions beyond the scope of the cities studied in this project.

Objectives

The objective of this project is to address central questions related to how travel behavior impacts from one-way shared mobility systems vary with land-use, multi-modal infrastructure, and urban travel patterns. Resources from the car2go dataset and other supporting data are being used to produce insights that are potentially generalizable to broader travel patterns, multi-modal behavior, and the integration of shared mobility with existing transportation systems.

Among the questions being addressed includes the following:

1. What is the spatial distribution of the impacts of car2go on modal shift, vehicles owned by the household, and driving?
2. How are observed shifts in travel behavior, as caused by car2go, associated with specific types of urban form and public transit infrastructure?
3. What can the distribution of behavioral shifts tell us about the urban and environmental ingredients needed for one-way car sharing and other shared mobility systems to have an effective impact on behavior (e.g., lowering private vehicle use, energy use, and emissions)? That is, systems like car2go mainly operate in cities, at a finer level of granularity; are there certain types of urban forms where some users make the decision to switch modes or avoid vehicles?
4. Are there certain types of environments where shared mobility is effective in facilitating a modal shift? What levels of public transit service are needed to provide enough multi-modalism for people to facilitate reduced car ownership in the presence of one-way car sharing?
5. Are certain patterns of home and work locations associated with modal shift in the presence of one-way car sharing?
6. How can the insights from the questions above inform projected impacts in the Smart City Challenge Finalist cities that have and do not have one-way car sharing? What other American cities might extract the greatest shifts toward multi-modalism from one-way car sharing that do not have it?

These research questions are being explored in five cities for which there are survey data of car2go users. These cities are San Diego, Seattle, Washington DC, Vancouver, and Calgary. Car2go extensively used BEV vehicles in at least one of these cities (San Diego). The insights from this effort are being projected on forecasting impacts that could occur within Smart Cities that do not have one-way car sharing. More broadly, the project is generating an understanding of how one-way shared mobility impacts behavior in different regions, which is critical for understanding how infrastructure and policy can maximize their energy impacts.

Approach

The project team for this analysis is composed of staff from LBNL and INL. Researchers will conduct data analysis using several sources of data. These include the following:

1. Survey data of about 9000 car2go users within five North American cities

2. Activity data from car2go to understand activity patterns at a more localized level
3. Data sources describing urban form, infrastructure, public transit systems and ridership.

Researchers are using location data within the survey responses to illustrate the spatial distribution of respondent home and work locations. These impacts are being then be mapped to the urban environments of residence and work locations. The data is being overlaid with other urban attributes including public transit infrastructure, public transit ridership, land use attributes, population density, and socio-economic attributes. The spatial alignment of these data is being used to draw associations between one-way car sharing impacts and urban form. The effort is aimed to establish insights on the environmental features that are conducive to having impacts from existing shared mobility and shared automated vehicle systems. The analysis is also evaluating how shifts toward multimodal behavior are associated with sociodemographic attributes of households, which was also collected in the survey. Researchers are also developing predictive models, currently with logistic regression and choice model structures, which can apply the attributes of the local environment to predict the potential impacts of one-way shared mobility within environments that do not yet have such systems. The project aims to use these models to provide some forecasting of impacts with select Smart Cities.

Results

Presently, results of the effort have entailed the geocoding of locations of survey respondents, and mapping impacts of car2go over the urban environment. Figure IV.4-1 presents examples of this mapping for the net change of public transit use in Seattle, Washington DC, and San Diego. These maps are examples of the types of impact mapping that, by themselves, is illustrative of the spatial distribution of impacts from shared mobility. Further analysis of these and other impacts is aiming to understand the type of urban and transit attributes that are associated with reported changes in both directions.



Figure IV.4-1 - Change in Transit within Seattle, Washington DC, and San Diego as Result of car2go.

This mapping is also being executed with changes in vehicle ownership, vehicle suppression (not acquiring a vehicle), changes in VMT, as well as changes in other travel modes. The modeling efforts are exploring the explanation of distributions of net changes in activity as well as the evaluation of uni-directional distributions of activity (e.g., the spatial distribution of only those who increase public transit use).

To enable infrastructure and transit comparisons, the team created a detailed list of potential data points that would be of interest to our research. In addition, we created a detailed document of data sources and contact information for 25 major cities in the USA and Canada, identifying the transit authorities and references as well as types of transit in each system. And we collected national data sources that would be of value to public transportation study.

For the five initial cities in the comparison study, we gathered detailed characteristics for the transit systems including monthly use and types of vehicles utilized. We have completed creations of a database to hold relevant route and characteristic data and collected the transit information into geographic regions. This database contains over 25 transit systems in the 5 regions, over 2,800 routes, 56,000 stops, and 575,000 trips. For the US cities, we have included elements such as land-use, density of population, access to employment, and urban design. The database currently holds over 24 million rows of data, with over 5 GB of information. The data is configured and available for GIS tool-set use and allows geographic queries as well as SQL and allows for evaluation at several levels of geographic design.

This dataset and geographic tagging allows us to examine characteristics that influence design and use of transit systems programmatically. For example, Figure IV.4-2 shows transit stops and routes relative to land use and total employment in Washington, DC.



Figure IV.4-2 - Transit infrastructure in comparison to land use and employment in Washington, DC

Future research will continue to compare geographic qualities, transit characteristics, and impacts of car2go use in regional settings.

Conclusions

The current effort has drafted a literature review of related research, fully geo-located the home and work locations of survey respondents, and engaged in spatial analysis of selected impacts. Furthermore, the efforts have identified resources for collecting comprehensive attributes descriptive of land-use and public transit attributes. It has further collected specific explanatory spatial attributes to advance the development of a fully linked data set. These efforts position researchers to engage in the modeling and estimation efforts defined for within the latter stages of the project. The output of this effort is expected to produce a cutting-edge spatial understanding of one-way shared mobility impacts that will help inform policy and infrastructure decisions within American urban environments seeking to foster improved mobility and smart city technologies.

Key Publications

Key publications are pending. Currently, the project has drafted a literature of review of shared mobility impacts and the urban and spatial attributes explaining those impacts. The literature review has found that research addressing this subject is sparse, reflecting the expected contribution of this work.

IV.5 National Scale Multi-Modal Energy Analysis of Inter-City Freight [Task 2.1]

Yan Zhou, Principal Investigator

Argonne National Laboratory
9700 S Cass Ave
Lemont, IL, 60439
Phone: (630) 252-1215
E-mail: yzhou@anl.gov

Victor Walker, Principal Investigator

Idaho National Laboratory
PO. Box 1625
Idaho Falls, ID 83415
Phone: (208) 526-8959
E-mail: victor.walker@inl.gov

Kevin Walkowicz, Principal Investigator

National Renewable Energy Laboratory
15301 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-4492
E-mail: kevin.walkowicz@nrel.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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Non-DOE share: \$0

Project Introduction

Trucking is the dominant freight-carrying mode in the U.S., carrying nearly three-quarters of all annual tonnage transported. Trucking is also the second least energy-efficient mode for freight transportation behind aviation. Potential exists for freight energy use to be reduced through the application of smart technologies (e.g., platooning) and optimization of freight movement through mode shifting (e.g., shifting from trucks to rail). This research revolves around the questions of “how could energy efficiency be maximized through the application of smart technologies and optimization of the freight network?”, and “what are the technologies and approaches which can impact the inter-city freight delivery, and how much impact could these changes potentially have on the over-all energy use for freight movement in the United States.”

Objectives

The primary objective of this research project is to quantify at the national level, energy and emission impacts of inter-city freight movement and opportunities for improvements in energy efficiency due to optimized modal shifting and the introduction of smart technologies.

A number of emerging smart technologies such as platooning have demonstrated the potential to improve trucking freight efficiency. However, platooning as a technology is limited by a number of factors, including the availability of platoonable ton-miles, the gap spaced between leading truck and following trucks, the number of trucks in platoon, the slope of road, traffic conditions, etc. As part of this project, the research team

will explore the opportunities and limitations of smart technologies such as platooning and document their overall potential for national scale energy impacts.

Approach

This project has utilized several key elements to better understand the impacts of inter-city freight changes at the national scale. We have worked to gather data associated with freight movement, verify baseline models (beginning with Argonne National Laboratory's NEAT model), and develop new scenarios which can then be used as inputs to the models to examine specific impacts.

The team has worked extensively with UPS (United Parcel Service) to partner on the collection of initial baseline data and to look at new approaches for freight delivery and movement. Representatives of each lab met with UPS leaders to gather information about their shipments, strategies, and energy use. The labs worked through a multi-party NDA which provided the groundwork for using UPS data as part of the project analysis and approach.

The team also gathered information from NREL's FleetDNA database and leveraged the Department of Transportation's freight movement databases as a foundation for the future modifications of the scenarios.

Initial efforts utilize Argonne's NEAT model to identify "size of the prize" of inter-city freight. The NEAT model estimates energy demand from non-light duty freight modes through 2050. NEAT has been developed to provide estimates of the potential end-use energy consumption, upstream energy consumption impacts through 2050 of a Base Case and user defined alternative case(s) relating to five domestic freight carrying modes and their use of alternative fuels. The five modes are: (1) Intercity freight-carrying Trucks, (2) Freight Rail, (3) Domestic Freight Marine, (4) Domestic Freight Aviation, and (5) Pipeline. The tool consists of a Microsoft Excel© workbook that contains Base Case estimates of U.S. freight mode energy use and carbon emissions to 2050. This file can be modified to reflect alternative assumptions about commodity ton-mile changes, mode share changes, modal energy intensity changes, alternative fuel market penetration, and electricity generation mix for pipeline compressors.

In an initial analysis, the team reviewed literature, real-world data and Smart CAVs pillar analysis/modeling results to establish limits to the following factors due to futuristic inter-city freight operations and smart technologies

- upper limits of truck efficiency due to platooning
- possible platoonable mileages
- possible future mode shares due to increasing demand on fast shipping
- Incorporated results from literature and CAVs pillar analysis to Argonne's NEAT model to quantify possible national energy impacts

Based on available research results, the team made the following assumptions in the analysis:

- Platoonable ton-miles increase from 0% to 65% over the time horizon of 2015 ~ 2040
- Energy intensity (BTU/ton-miles) decrease 4% for leading trucks and 10% for following trucks. On average, one leading truck is followed by 3 following trucks
- Sensitivity analysis: the platoonable ton-miles varies from 50% ~ 80% at 2040
- Analysis horizon: 2016- 2040

All assumptions are based on literature and SMART MOBILITY results, will be updated when better information is available within the pillar and from other pillars.

Future scenarios will examine scenarios which take into effect the shifting of freight from one mode to another (using capacity constraints), the introduction of further Next Gen Truck technology (such as power-train improvements, Automation, Parasitic losses, Dead-heading, and Full EV trucks.), and new business models such as just-in-time distribution centers.

Results

The team identified the following research gaps in existing field testing and simulation studies:

- Very few studies investigated the truck efficiency change by commodity type
- Limited studies on the amount of time and distance available for platooning
- Limited studies on the fuel savings or increase in platoon formation
- Limited information reported on payload (weight of truck) and commodity types when platooning
- Limited studies on fuel savings potential of individual trucks making a trip that are a part of platoons along the way
- Most of the experimental studies have been conducted on empty roads (no traffic congestion) with trucks that are the same weight

We summarized the truck fuel saving due to platooning and platoonable miles based on existing field testing and simulation/modeling studies.

Truck Fuel Saving Due to Platooning Varies in a Wide Range

- Lead Truck: 2%-7%
- Trail Truck: 3%-16% depending on gap
- Tandem fuel saving: 3%-15% depending on gap and # of trucks
- Trucks should be ordered based on mass for maximum fuel efficiency
- Shorter spaces in between trucks lead to greater fuel savings
- Reported saving are averaged out so that slope of road is not taken into consideration
- Fuel efficiency in the formation of platoons: adjusting speeds for the splitting and merging of platoons is still more efficient than not being a part of a platoon at all

Platoonable Miles/Time Vary by Speed and Continuation Beyond Certain Speed

1. SMART CAVs/9E NREL report: platoonable miles by time thresholds (amount of time continuously driven above 50 mph)
20% - 85% platoonable miles (2 min – 90 min)
2. FHWA/AUBURN study: developed optimization algorithms to better understand what affects platoon formations

- Lead truck speed adjustment influences number of platoons could be formed, but increase time delays
- Energy consumption of accelerating when forming could cancel out the benefits of a platoon
- Road saturation affects platooning opportunities – more trucks on road within smaller distances between them can lead to more platoon formations

Annual inter-city freight sector energy consumption could be reduced by about 4.2% due to truck platooning in 2040, shown in Figure IV.5-1. Sensitivity analysis shows that annual freight energy consumption (upstream included) could be reduced by ~ 5% due To truck platooning in 2040 (Figure IV.5-2). An earlier analysis Argonne did in FY16 with DOE VTO support indicates mode shift from truck to rail could reduce truck energy consumption by additional 6% in 2040. Cumulative freight sector total energy saving (2016-2040) due to truck platooning could be up to 5,330 Trillion BTU (upstream included), shown in Table IV.5-1.

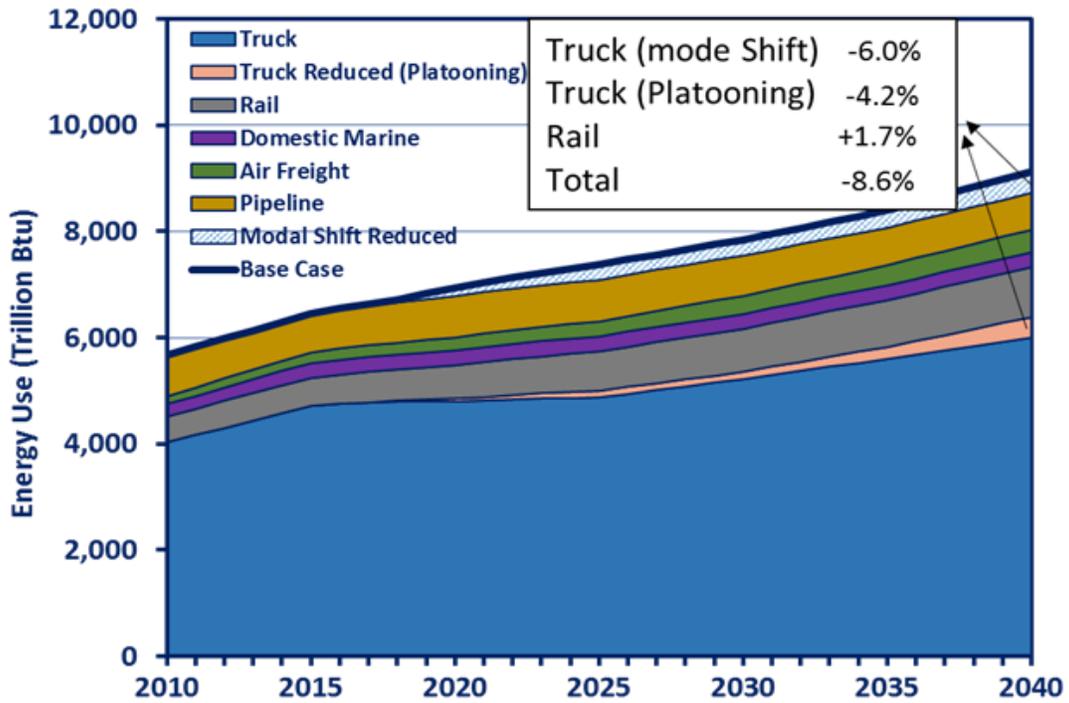


Figure IV.5-1 - Freight sector total energy reduction due to platooning and mode shift

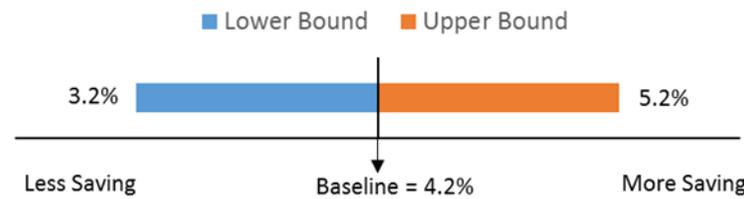


Figure IV.5-2 - Sensitivity analysis for energy saving due to platoon at 2040

Table IV.5-1 - Cumulative Energy saving

		Low	Medium	High
Total Energy Use (Trillion BTU)	Value	3331.1	3816.8	5329.8
	%	1.5%	1.7%	2.3%
GHG Emissions (Million MT CO2 Eqv)	Value	284.9	326.3	455.8
	%	1.4%	1.6%	2.3%
Upstream Energy Use (Trillion Btu)	Value	765.9	877.2	1225.4
	%	1.5%	1.8%	2.5%

Conclusions

Cumulative freight sector total energy saving (2016-2040) due to truck platooning could be up to 5,330 Trillion BTU. Annual freight sector energy consumption (upstream included) could be reduced by about 4.2% due to truck platooning in 2040. Energy savings and emissions reduction are sensitive to % of platoonaible miles and average tandem fuel saving (e.g., # of the trucks, truck gaps). Sensitivity analysis shows that annual freight energy savings could vary from 3.2% to 5.2% in 2040.

For next step, the research team will further investigate the possible platoonaible miles/times available, however to the best of our knowledge studies in this topic are very limited. Also, the team will incorporate results and data from other members within the Multi-modal pillar and CAVs pillar to characterize benefits from key Smart Mobility technologies (e.g., FleetDNA, UPS data).

For FY 2018, the team will identify efficiency improvement due to other smart technologies beyond platooning, as well as opportunities provided by electrification technologies, resulting in updated estimates for the energy impacts of additional technologies on inter-city freight. The team will also project future inter-city freight demand due to increasing fast/guaranteed shipping (demand higher than AEO/FAF projections).

Key Publications

1. Meetings / Conferences: Y. Zhou presented “National Scale Multi-Modal Energy and GHG Analysis of Inter-City Freight,” at 2017 DOE VTO Annual Merit Review Meeting, Washington D.C., June 5-9, 2017.
2. Presentations: ANL’s preliminary analysis results were highlighted in a presentation, Overview of Platooning Activities for Commercial Trucks, by Roland Gravel of VTO to the SuperTruck Partnership meeting in September 2017.

IV.6 Inter-City Freight Movement Optimization Model and Data [Task 2.2]

Tim LaClair, Principal Investigator

Oak Ridge National Laboratory
2360 Cherahala Boulevard
Knoxville, TN 37932-6472
Phone: (865) 946-1305
E-mail: laclairtj@ornl.gov

Kevin Walkowicz, Principal Investigator

National Renewable Energy Laboratory
1617 Cole Boulevard
Golden, CO 80401
Phone: (303) 275-4492
E-mail: Kevin.Walkowicz@nrel.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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DOE share: \$275,000

Non-DOE share: \$0

Project Introduction

Advances in technologies, new business models, and much greater availability of transportation data will change the way that people and goods move, introducing new opportunities for the reduction of energy consumption. A variety of advanced vehicle technologies and new operating practices offer very significant potential to reduce the energy consumed in freight transport. Nonetheless, fleet managers and procurement personnel are not always aware of the benefits of many of these technologies, and the magnitude of the energy savings potential may be unclear under different operating conditions. Such uncertainty limits the acceptance of new technologies and can act as a barrier to widespread implementation in vehicle fleets. In the transportation industry, even technologies that have been demonstrated to yield significant fuel savings often are not rapidly deployed due to a lack of understanding of how energy savings might vary in different usage cases, for example in different trucking vocations, specific vehicle applications or across varying driving conditions. To help promote new technologies and encourage the adoption of those providing the greatest benefits, it is desirable to quantify the energy savings for users' actual usage and to provide a relatively simple means to evaluate a range of technologies, including combinations of technology.

As part of the U.S. Department of Energy's (DOE) Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Initiative, the Oak Ridge National Laboratory (ORNL) has led a study to develop an easy-to-use, web-based model that will enable vehicle fleet operators to quantify the energy savings achievable by implementing advanced transportation technologies. By developing a profile of a fleet's existing vehicle inventory and providing data about how the vehicles are driven, fuel consumption can be calculated for the entire fleet, and users can perform "what if" scenarios to evaluate the energy savings that can be achieved when replacing existing vehicles and implementing new technologies. The model will account for vehicle usage by evaluating both speeds and road grades so that the energy use is calculated based on driving conditions that are representative of those experienced by the fleet. This tool aims to assist those responsible for fleet procurement and operations to select alternative fuel/energy efficient vehicles and technologies and to quantify the energy savings provided by these vehicle/technology selections, including the implementation of various connected and automated vehicle (CAV) technologies.

Objectives

Under this project, an underlying goal is to evaluate national and regional energy impacts associated with inter-city freight efficiency improvements and possible mode shifts, and to assess the impacts of SMART Mobility and other advanced vehicle technologies on freight fleets as well as identify opportunities for reducing energy use via these technologies. An initial objective in FY 2017 was the development of a model capable of estimating commercial freight energy consumption at the fleet level inclusive of current and near term innovative SMART transportation systems and alternative technology considerations. The Freight Fleet Level Energy Estimation Tool (FFLEET) was developed to calculate energy savings based on the difference in energy consumption between an existing fleet and future scenarios for deployment of advanced vehicle technologies. The work plan included a review of current scientific research on energy saving vehicle technologies and models, particularly the research underway or completed by the national laboratories. Using the most up-to-date science and modeling approaches, FFLEET will facilitate evaluation and selection of innovative SMART transportation systems and other advanced vehicle and alternative fuel technologies.

Other planned activities for the project include identifying new freight transportation modes and advanced inter-city freight movement technologies, and evaluating their potential benefits using city planning tools including FFLEET to identify scenarios for reducing energy consumption for inter-city goods movement.

Approach

The project team for this analysis was composed of staff from ORNL and NREL.

FFLEET was developed as a web-based tool, with the goal of providing easy-to-use and accurate, science-based estimates of the energy savings that a freight fleet can achieve when employing advanced transportation technologies. The tool is intended for users that do not necessarily have any expertise in vehicle simulations, so ease of use was a primary consideration in the tool's development. Nevertheless, FFLEET allows evaluations of a broad range of technologies based on a fundamental energy-based evaluation of vehicle operation. Several options for specifying the vehicles are available based on the specific needs of the user and the availability of data. For example, a very accurate calculation of energy consumption can be obtained if both detailed vehicle specifications are available and accurate usage data can be provided. Relevant vehicle specifications include the aerodynamic drag coefficient, frontal area of the vehicle, tire rolling resistance coefficient, vehicle mass (including typical variations in loading that occur) and a detailed characterization of the propulsion system. The usage data could be provided based on measurements of vehicle speeds and road grades representing the driving conditions encountered by each vehicle in the fleet. While such detailed data will generally enable more accurate evaluation of a particular vehicle, lack of this type of detailed specification data for the entire fleet should not hinder a user from obtaining a reasonable estimate of the energy savings that can be achieved by implementing new technologies and identifying the technologies that will yield the greatest energy savings benefits for a particular application. Therefore, alternative options are provided in the tool to select vehicles that are representative of typical configurations and select drive cycles without very specific data.

FFLEET is unique in that it is intended to allow users to estimate energy savings for an entire fleet of vehicles, and it will permit energy savings to be quantified in stages if vehicle replacements or other vehicle technology implementations will be done at different points in time. In addition, smaller groups of vehicles, such as those representing a particular use or a set of vehicles that are based at a particular location, can be evaluated and the vehicle groups can then be combined to aggregate the results for larger groups or the entire fleet, as desired by the user. Individual vehicle evaluations can be completed as well, and the results from a full-fleet assessment can be reviewed at the level of smaller vehicle groups or at the individual vehicle level. This provides the user with a high degree of flexibility for performing the energy savings evaluations and considering the benefits at different scales.

The calculation of the energy savings for the fleet is done by directly calculating the difference in energy consumption for all vehicles in the fleet in both an initial and a final fleet configuration state. The vehicles

included in the fleet’s inventory for the initial and final states must be specified, along with specifications of the driving characteristics for the vehicles. These can be entered using a hierarchical approach that provides flexibility in terms of how data are entered for both the vehicle and its usage, and it allows usage specifications to be reused for different vehicles that have similar driving characteristics or, conversely, if the same types of vehicles are used in different driving situations.

The energy consumption calculations are based on a simplified vehicle powertrain model corresponding to the selected powertrain type that uses drive cycle data to characterize the driving characteristics of each vehicle. The tractive power required to propel the vehicle is calculated at each point in time using the specification data and the drive cycle inputs, and component efficiencies are used to determine the energy use from the primary energy source(s) (fuel and/or electrical energy) corresponding to each vehicle’s powertrain. In this manner, the model accounts for the energy flows/conversions/losses for the fuel, the powertrain components and the overall vehicle using a physics-based evaluation. A literature review was conducted at the beginning of the project to identify models and approaches used in other tools, and the methodology employed follows commonly accepted methods for vehicle powertrain modeling [1-6]. We note that the same underlying vehicle model is used both for FFLEET and for the passenger vehicle model SVET developed in the project “Develop Smart Vehicle Energy Technology (SVET) Passenger Fleet Model,” which is also described in this FY2017 Annual Progress Report. Fundamental differences in user needs, relevant technologies and the basic use cases between the passenger and freight-hauling vehicles resulted in the development of separate tools, but the methodology used for the vehicle model remains very similar for both tools. The selection of parameter values used for the various technology selections were also based on data contained in the literature [7, 8].

The drive cycle-based powertrain modeling approach allows a broad range of technologies to be evaluated, and the results of the analysis are specific to the selected vehicle configuration and the usage defined by the drive cycle so that the user is able to quantify the benefits that can be achieved for a particular technology implementation for the type of driving that is done and for the types of vehicles that operate within the fleet. The parameters for the various vehicle components are modified in the model to account for technologies that function by directly changing the vehicle or powertrain characteristics, while technologies that impact how the vehicle is driven can be accounted for by modifying/filtering the drive cycle data in a manner representative of the deployed technology. This approach of modifying the drive cycles allows a simple evaluation of technologies such as speed governors and various connected and automated vehicle (CAV) applications using the same modeling approach, without the need for elaborate traffic simulations to be implemented in the tool.

The primary activities for this project in FY 2017 were focused on the FFLEET model development (led by ORNL) with support provided by NREL, who also compiled data regarding existing inter-city freight technology and corresponding freight efficiency based on analysis of NREL’s Fleet DNA database. UPS is an initial partner for evaluating the model and providing data for SMART Mobility inter-city freight evaluations. The team also plans to work with other freight transport providers in the future to obtain more diverse data and alternative perspectives that are likely to come from considerations of different freight applications.

Results

The FFLEET tool was designed to allow users to enter vehicle specifications in multiple ways based on either direct entry of parameter data or using a set of selections for the vehicle type, propulsion system, some common aerodynamic drag options, tire rolling resistance levels, and transmission. Table IV.6-1 presents the vehicle technology options that users may select using the FFLEET user interface.

Table IV.6-1 - List of Vehicle Technology Options Available in FFLEET

Vehicle types:
Class 7-8 tractor-trailers (day cabs and sleeper cabs)
Box/straight trucks
Delivery/step vans
Car carriers
Flatbed trucks
Propulsion systems:
Conventional internal combustion engine (gas, diesel, or natural gas)
High pressure direct injection (HPDI) engine (dual fuel natural gas-diesel)
HEVs (hybrid electric vehicles)
PHEVs (plug-in hybrid electric vehicles)
BEVs (battery electric vehicles)
CAV technologies:
Traffic signal eco approach and departure
Connected Eco-Driving
Platooning
Other fuel efficiency technologies:
Aerodynamic drag reduction devices (advanced cabin fairings, trailer skirts, boat tails, trailer gap reduction, under body drag reduction, wheel covers)
Low rolling resistance tires
Speed limiters
Auxiliary Power Units (APUs)
Advanced transmissions: 6-18 speed options
Vehicle Lightweighting options (e.g., carbon fiber body panels, low mass glider, compacted graphite iron (CGI) block)

The technology options are selected through a web-based graphical user interface (GUI) using common input formats so that it will be easy for users to understand and make their selections. The tool uses the input selections to determine appropriate vehicle model input parameters to characterize the vehicle specified. Figure IV.6-1 shows a screenshot of a technology selection page in the tool as presented in the graphical user interface.

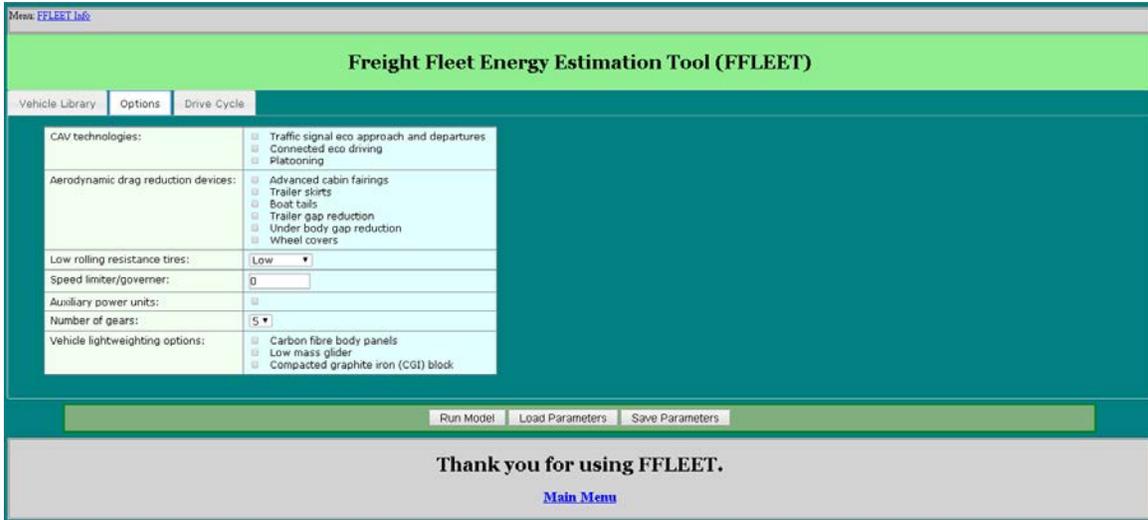


Figure IV.6-1 - Screenshot of a technology selection page in FFLEET.

The user may also manually enter the fundamental vehicle parameter values used in the model or override any inputs that are generated based on the technology selections. This provides added flexibility for users that are more familiar with vehicle specifications and know parameter values for a particular technology. The GUI for FFLEET stores all user inputs, indicates whether parameters have been modified by the user, and allows detailed descriptions to be entered in order to assist with model version tracking.

The primary output from a FFLEET simulation is the fuel consumption data. When a fleet evaluation is selected (i.e., multiple vehicles), output data will be provided to the user in a table summarizing the model results for all vehicles. In addition to the fuel summary data, the user may choose to create graphs showing individual vehicle results. Several graphs of modeling results from the vehicle analysis are available for display depending on the options selected. Figure IV.6-2 is a stacked plot that shows the vehicle speed along with results for engine speed and fuel consumption from a standard vehicle simulation. Similar graphs are available with key performance data plotted for any vehicle simulation.

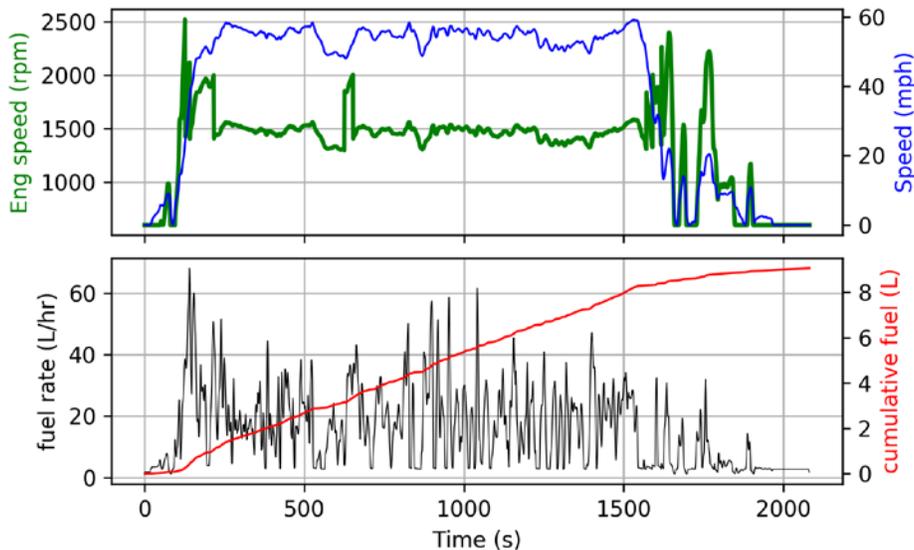


Figure IV.6-2 - FFLEET Model result showing the vehicle speed, engine speed and fuel consumption as a function of time

A unique feature of FFLEET is the inclusion of several drive cycle modification functions. The tool includes options to perform basic filtering of input drive cycles and elevation data so that noise and inaccuracies introduced by limited resolution in measured drive cycle data can be minimized using the drive cycle/elevation smoothing functions. In addition, when the user selects an evaluation with a speed governor or either of the CAV applications (Traffic Signal Eco-Approach and Departure (EAD) or Eco-Cruise), the FFLEET tool performs a drive cycle modification before running the vehicle model. This speed modification is intended to represent the change in driving that the selected function will generate. In the case of the speed governor, any speeds in the original drive cycle that exceed the limit speed set point (as selected by the user) are restricted to the limit value for all locations where the vehicle in the initial drive cycle was driven at higher speeds. This results in a longer driving time to cover the same distance, as shown in the comparison of the governed speed plotted as a function of both time and distance (Figure IV.6-3).

For the EAD and Eco-Cruise options, the drive cycle is modified to replace periods of braking with coasting so that the braking is minimized or eliminated. The EAD application is aimed at decelerations during approaches to lighted intersections, whereas Eco-Cruise aims to coordinate speeds between vehicles during regular driving, away from signaled intersections. Figure IV.6-4 shows an optimized drive cycle with most braking eliminated throughout the driving, representing a combined Eco-Cruise and EAD operation.

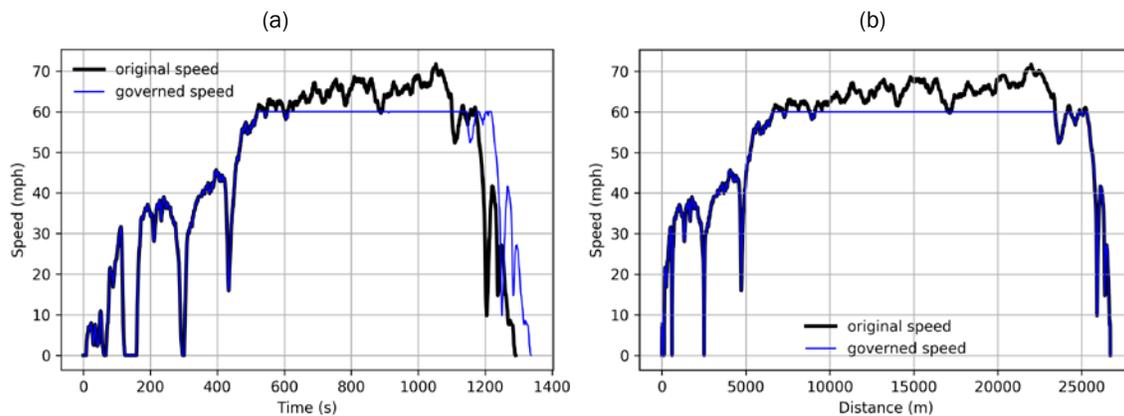


Figure IV.6-3 - Governed speed drive cycle modification as a function of (a) time and (b) distance, showing the longer time spent at the reduced limit speed to cover the same distance driven in the original cycle

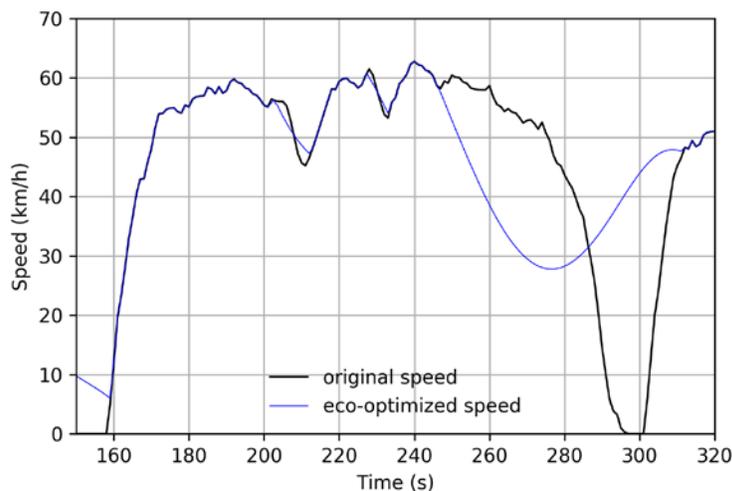


Figure IV.6-4 - A segment of an optimized drive cycle representing combined EAD and Eco-Cruise operation. Braking is completely replaced with coasting during this optimized drive cycle

Conclusions

In FY 2017, the main objective under this project was the development of the FFLEET model, which is a web-based software tool aimed at estimating the energy savings achievable in freight fleets when implementing advanced vehicle technologies. The tool allows users to enter a profile of a fleet's existing vehicle inventory and provide vehicle usage data, and FFLEET will calculate fuel consumption data for the entire fleet. Starting with the initial vehicle inventory profile, the user can perform "what if" scenarios to evaluate the energy savings that can be realized when replacing existing vehicles and implementing new technologies. This tool was designed for ease of use and will assist those responsible for fleet procurement and operations to select alternative fuel/energy efficient vehicles and technologies and quantify the energy savings provided by these vehicle/technology selections, including the implementation of various connected and automated vehicle (CAV) technologies.

Key Publications

1. T. LaClair, D. Davidson, "Passenger and Freight Fleet Energy Saving Models for SMART Mobility" (literature review of vehicle powertrain models and a detailed description of objectives for the FFLEET and SVET models), submitted with the FY 2017 Q1 Quarterly Project Report to DOE, Jan. 2017.
2. T. LaClair, "Functional Specification for the FFLEET Web-Based Tool," submitted with the FY 2017 Q1 Quarterly Project Report to DOE, Jan. 2017.

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IV.7 Optimization of Intra-City Freight Movement and New Delivery Methods [Task 3.1]

Amy M. Moore, Principal Investigator

Oak Ridge National Laboratory
2360 Cherahala Boulevard
Knoxville, Tennessee 37932
Phone: (404) 625-4661
E-mail: mooream@ornl.gov

Kevin Walkowicz, Principal Investigator

National Renewable Energy Laboratory
15301 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-4492
E-mail: kevin.walkowicz@nrel.gov

Victor Walker, Principal Investigator

Idaho National Laboratory
PO. Box 1625
Idaho Falls, ID 83415
Phone: (208)526-8959
E-mail: victor.walker@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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DOE share: \$200,000

Non-DOE share: \$0

Project Introduction

The objective of this task is to provide an analysis of opportunities for emerging and novel intra-city goods delivery modes. Given the quickly changing transportation market and the rapid development of new technologies and business models, there is great potential for dramatic changes in the energy use in freight delivery in cities and “last-mile” models. New approaches such as the “uberization” of delivery, just-in-time delivery, hub-based drops, as well as the deployment of advanced vehicle technologies such as connected and automated vehicles, and alternative fuel sources (i.e., H2, EV, etc.) create a wide range of technology disruptors with the potential to significantly change the landscape of goods movement.

Within this task, researchers will seek to develop an understanding of these new technologies while also assessing their efficacy through analysis of existing intra-city delivery behavior and modalities. As part of the analysis efforts, baseline data for all modes of intra-city freight delivery will be gathered, and new models will be generated that can provide more effective and accurate projections of energy and infrastructure impacts in these areas.

To validate the analysis approach, this effort may leverage existing or new UPS data to baseline actual logistics business model attributes (consideration of package size, handling equipment, modes of conveyance, transfer, pickups/deliveries/stem routing, time, etc.).

Objectives

This project provides important analysis of the impacts of new and emerging business models and technologies. Accomplishing this primary objective requires the development and deployment of several new models, data techniques, and analysis approaches for intra-city freight deliveries.

Characterization and optimization of intra-city freight movement (modes and technology) will allow cities such as Columbus, Ohio to define the energy and associated emissions impacts of ‘SMART’ transport of freight within their city. It is understood that new intra-city modes will impact future infrastructure and spatial energy demand of a city, however limited research has been completed to quantify and forecast the potential impact on overall energy efficiency and consumption. Having proven models, data structures, and analysis techniques will allow city planners and associated commercial partners to have a system-level understanding of the technology, consumer choices, and the impacts on a planned urban environment.

To facilitate this research, ORNL will work in collaboration with INL and NREL to develop a tour-based model for freight delivery for city scale analysis and optimization.

Additionally, NREL, working with ORNL and INL, will develop a micro-scale travelling salesman based model to integrate the scenarios associated with hub and spoke delivery models, explore small scale route behavior and optimization, and examine opportunities for energy efficiency improvements and savings on a vehicle-by-vehicle level.

As part of the model development process, the project will also gather new data associated with freight transportation. Participating labs will work with partners to gather data associated with intra-city delivery and find ways to better identify routing and package handling impacts.

INL will also be leading efforts to perform experiments gathering data associated with drone energy use and profiles to help characterize this future mode of delivery and understand its application and scope.

Approach

The project team is composed of staff from ORNL, NREL, and INL. This project will focus on three primary activities to meet the goals and objectives: data collection and experimentation, business and tour-based modeling, and scenario development and testing.

Data Collection and Experimentation:

The project will work with partners such as UPS to gather data associated with freight deliveries. In addition, another strategy to understand parcel-level freight movement involves shipping GPS trackers through several different methods.

To support model development, the project will also include capturing and documenting improved data associated with fuel use and utilization of current and future intra-city delivery vehicles.

The project will also perform experiments on delivery drones to characterize the use of drones in freight delivery business models and what the impact of these drones will be on total energy needs for delivery.

Business and Tour-Based Modeling:

The project will integrate a traveling-salesman model that will look at different delivery methodologies that can then be integrated into higher scale tour-based models. The microscale model developed by NREL leverages existing data drawn from DOE’s Fleet DNA commercial vehicle database, as well as data that will be captured during the project, to forecast energy consumption and optimize vehicle routing under a number of different scenarios.

The prototype Tour-Based Freight Model will be developed for the Mid-Ohio Regional Planning Commission (MORPC), the MPO for Columbus, Ohio. ORNL and INL will work closely to identify the types and

availability of data needed to populate an innovative local tour-based framework and complete development. A white paper by ORNL on existing Tour-Based Freight Modeling, as well as a white paper containing the framework for implementation in FY 2018 for Columbus, Ohio was developed in FY 2017.

Scenario Development and Testing:

The project will identify critical scenarios that will be used for testing and analyzing the models, which represent potential future business operations and technology introduction. These will identify which specific questions will be most relevant for our reporting and will result in publications and reports demonstrating potential changes and recommendations on how to best prepare for and take-advantage of these changes.

Results

Data Collection and Experimentation:

The team met with UPS (United Parcel Service) and completed a multi-party non-disclosure agreement to utilize data from UPS in gathering and processing information that will lead to improved modeling and analysis capabilities.

The project has obtained GPS tracking and logging hardware which it has successfully shipped to several locations and recorded the overall performance of the delivery methods, which demonstrates the completed paths through different delivery modes and vehicles. This data can be utilized to create modeling scenarios and identify differences in freight deliveries by mode and provider.

Analysis has been done to understand and create statistically significant speed versus fuel consumption metrics in order to easily assess specific vehicle usage and specify the correct per mile energy consumption (which can vary depending on route/duty cycle of the truck). Sensitivity and regression analysis studies were performed to understand R2 values of various datasets. These data sets (for all available ‘last mile’ modes) will be used as input in multi-modal analysis models when considering mode and route options.

In order to obtain and utilize specific Columbus data for analysis in this task, NREL deployed 30+ data loggers to the Columbus hub, which captured origin and destination data for package delivery vehicles. This data will be used to understand the ‘baseline’ or traditional delivery method and opportunities to use various multi-modal scenarios and reduce, time and fuel consumption. Additionally, this data is being used to assist the development of the microscale traveling-salesman model which will be integrated with the city scale tour-based model.

Business and Tour-Based Modeling:

After completion of a comprehensive literature review, it was determined that the methodology used to develop the tour model will be an extension of methods used in existing tour-based freight models and regional-level travel demand models. Caliper’s TransCAD software, which is used by many MPOs and regional planning entities to develop travel demand models, will be used to develop the model. Regression analyses will be performed in TransCAD to estimate the number of origins and destinations/stops per Traffic Analysis Zone (TAZ) in Columbus (see Figure IV.7-1). The UPS data will be used to understand the typical number of stops per tour. A shortest path routine will then be used to determine the route based on: the limited distance (estimated 30-mile radius from tour origin for intra-city), the maximum number of stops, and the tour type (retail, manufacturing, food service, residential, etc.). The actual route will be determined based on congestion associated with the road network segments, using data on average speeds from the UPS GPS data, and any other available data (Average Annual Daily Traffic, or AADT, forecasted traffic data from MORPC, etc.). Once the radius from the origin is specified, and the number of TAZs determined as stops for a specified tour-type are estimated, the route will be determined simply using the TransCAD routing function, which is based on Dijkstra’s Algorithm, which will select road network links based on the travel time (cost) associated with each link. The route will be selected based on the least-cost path, making “stops” at each TAZ designated

as a stop, and returning to the origin TAZ. TAZs with higher estimates of tour destination/stops will be selected for case study analyses to incorporate new freight modes and technologies to estimate energy savings.

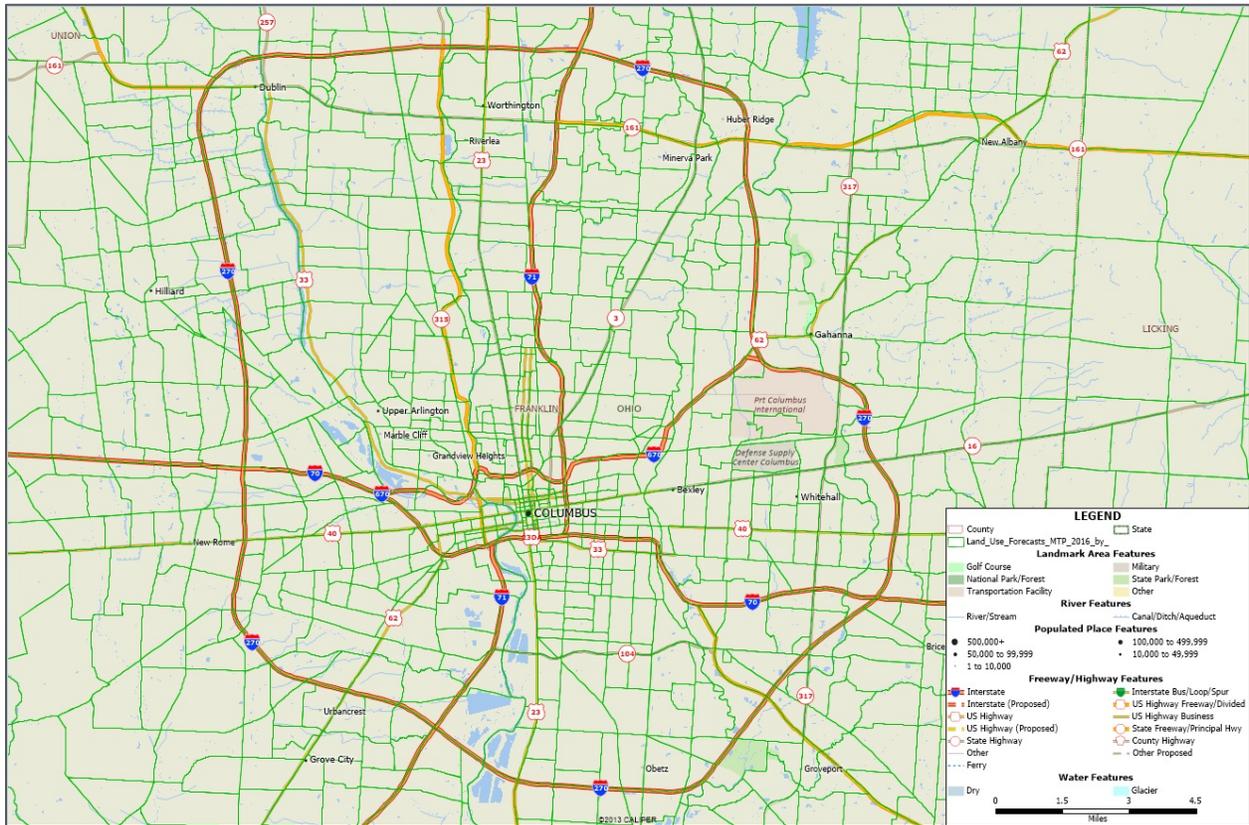
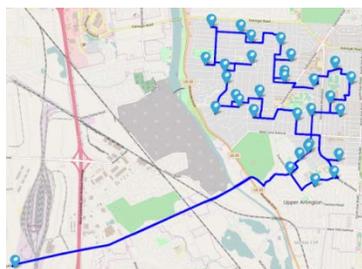
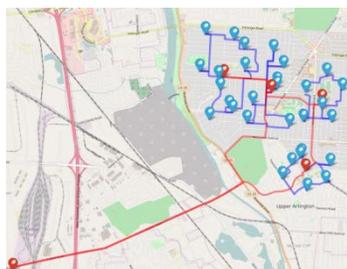


Figure IV.7-1 - TransCAD Interface Showing Columbus, Ohio

In addition to the efforts completed to initiate the development of the Tour-Based model, NREL researchers successfully developed an initial microscale traveling salesman based route optimization and evaluation model. This model uses existing and modified tools to estimate intra-city multi-modal freight energy consumption and emissions based on volume and specific movements under a variety of user defined scenarios. Google API data is used to understand baseline versus optional delivery routes incorporate multi-modal “scenarios”. Example output of this approach is shown in Figure IV.7-2.



Total Distance: 21.5 miles
Total Travel Time: 71.1 mins



Total Distance: 27.5 miles
Total Time 39.6 mins

	Baseline	Autonomous EV	Savings
Total Distance (mile)	21.5	27.5	+28%
Fuel Powered Distance (mile)	21.5	13.2	-39%
Electric Powered Distance (mile)	NA	14.3	
Total Travel Time (min)	71.1	39.6	-44%
Total Fuel Equivalent (gal)	2.2	1.8	-18%

Comparison of mode choice

Figure IV.7-2 - Example delivery model changes from traditional to hub-based delivery

For further enhancement and understanding of technology performance, initial development of a route based predictive drive cycle model is underway. Using origin-destination routing information as inputs, this model will generate a representative drive cycle (or estimation of speed/time) which can then be input into various existing DOE Tools to predict higher accuracy energy usage estimations along a route.

Scenario Development and Testing:

The project has identified the following high-level scenarios as initial representations of the goals of the project:

Scenario 1 - Traditional

Utilize current technology and approach, such as movement of a conventional vehicle directly from centralized delivery center to the final destination.

Scenario 2: Distributed Hubs to Energy-Efficient Vehicles

Utilize conventional or larger vehicles to distributed hubs throughout a city; Shift to personal vehicles (EV) to delivery from hubs to final destinations.

Scenario 3: Smart Locker Hubs

Utilize conventional vehicles to distributed smart lockers; Consumers utilize personal vehicles to collect packages – usually in conjunction with another trip.

Scenario 4: Drone Delivery

Utilize drones to deliver packages either from distributed hubs or from a conventional vehicle. Scenario 5: Personal Vehicle Delivery

Utilize contract drivers with energy efficient vehicles to deliver packages from the centralized center to the final destination.

Conclusions

The initial work in this area has identified the critical importance of understanding the impacts of future delivery methods for “last-mile” intra-city freight and goods. The business models and technology in this area are undergoing radical changes and the impact may be dramatic. Our efforts in gathering data and developing models which can perform much more detailed analysis appears to be critical to understanding the future of transportation energy use in cities.

Key Publications

1. Modeling Energy-Saving Freight Delivery Scenarios – Energy, Utilities, and Environment Conference Journal (accepted for publication and presentation)
2. A Compendium of Tour-Based Freight Modeling Literature (RESolution – ORNL’s publication system)
3. Proposed Methodology for a Tour-Based Freight Model (RESolution – ORNL’s publication system)

V. SMART Mobility – Urban Mobility Science

V.1 Mobility Data & Models Informing Smart Cities for Urban Travel, Land Use and Infrastructure Transitions [Tasks 2.1 & 2.2]

Joshua B Sperling, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway, MS 1625
Golden, CO 80401-3305
Phone: (720) 646-2884
E-mail: joshua.sperling@nrel.gov

John M. Beck II, Principal Investigator

Idaho National Laboratory
2525 Fremont Avenue, MS 3710
Idaho Falls, ID 83415
Phone: (208) 526-3433
E-mail: john.beck@inl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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Project Introduction

The Urban Science pillar focuses on increasing energy productivity (maximizing mobility while minimizing energy intensity) through research and analyses for urban travel, land use, and infrastructure transitions, to inform how (and where) to best enhance mobility choices associated with emerging technologies and services. Goals include addressing data and knowledge gaps to further enable the energy efficient movement of people and goods, increase accessibility, convenience (e.g., on-demand choices), affordability, and improve quality of life in urban areas. The foundational task in this area first concentrated on curating (that is collecting, organizing, processing, storing, and now analyzing) the available and evolving data and data-informed modeling environments of *the seven US DOT Smart City finalists*, and their respective energy efficient mobility research and investment priorities that focus on emerging and disruptive mobility technologies and services (e.g., automated, connected, efficient, shared mobility) in urban areas. This foundational task is intended to enable efficient access to the data, models, and knowledge generated from Smart City peer cities and to share data, analysis, benchmark progress, and fill key knowledge gaps relevant to the DOE Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium.

Objectives

The objectives of this task, within the larger U.S. Department of Energy (DOE) SMART mobility initiative, is three-fold: to 1) provide cross-city data platforms to visualize, interpret and extend the available resources to explore city mobility; 2) harmonize methods and approaches to data integration, visualization, and model-driven analyses; and 3) down-select on city case studies to work together on the testing and scaling of DOE science towards solutions with local city and regional partners focusing on addressing specific knowledge and data gaps. These activities aim to align with other SMART Mobility pillars by targeting specific urban mobility metrics (e.g., travel time) and associated energy impacts (e.g., BTU per vehicle and passenger miles

traveled) and related data collection focused on new urban automated, connected, energy efficient and shared mobility strategies developed and evaluated with partner cities, where knowledge generated and coupled mobility-energy assessments can advance efforts across all 498 U.S. urban areas. The aim is to first explore the literature, new and existing data sets, and data-driven modeling and analysis environments with US DOT Smart city finalists in year one, and then upscale effort in year two and after with efficient access to this curated urban data and models, to create new relevant analyses on urban travel, land, and infrastructure transitions and the associated energy and mobility impacts.

Approach

The primary year one deliverable was a task to curate (that is to collect, organize, process, store and analyze) the evolving data and transportation modeling environments informing the USDOT Smart City Challenge finalists which include seven cities: Columbus, Ohio (winner from the grant), Denver CO, Pittsburgh PA, Portland OR, San Francisco CA, Austin TX, and Kansas City MO. In particular the state of the data infrastructure and the initiatives to create a 'data-driven' city information architecture to support smart city objectives, particularly in the mobility-energy space, as well as the maturity of existing travel models to assess impact of emerging mobility technologies and services were of primary concern. As part of the Curation of Data and Models deliverable, the Urban Science team has held meetings and focus groups with the smart city finalists for data collection and insights for next analyses. This included on-sight meetings at San Francisco (as well as Oakland), Pittsburgh, Denver, Portland, and Austin, and planned meeting in Kansas City in 2018. Initial data collection/analysis is informing future research coordination as part of FY 2018 AOP with smart city partners. The engagements are opening opportunities for data sharing and new data collection on energy efficiency interventions relevant to SMART mobility, and access to urban/regional model resources under development with new survey results. A draft of the 'Curation of Data and Models Informing Smart Cities' is under internal review and on schedule for external distribution in early 2018. This includes emphasis on the transportation models and supporting data, benchmarking of existing travel models and data, and analysis focused on future transportation energy impacts from initial projects by smart cities and their wide ecosystem of stakeholders. This has formed the foundation for the Urban Science Pillar to move forward with multiple FY 2018 research and analysis- driven papers.



Figure V.1-1 - Timeframe of Engagement with Smart City Challenge Stakeholders

Results

The primary conclusions from this data and model curation task are shared below. Some of these areas of opportunity are already being acted upon through existing or planned research activities in the fiscal year 2018 Urban Science portfolio of projects, while others are identified as priorities areas. Key takeaways from this effort include:

- The variation and diversity of each city informs key motivating factors for smart city initiatives, as well as analysis needs and critical data gaps. Local context is critical with respect to a cities' capacity, resources, and motivation to pursue not only smart city pilot projects, but also to enhance their data infrastructure and modeling capability. Identification of key pilots within smart cities can help with research and data collection opportunities to analyze the pre- and post-implementations, to measure

effectiveness of different advanced mobility strategies, and to create a more robust evidence base for future smart city investments.

- The need for a robust data sharing and exchange platform is a common theme and initiative within all seven smart cities. Most cities are pursuing this through collaborative efforts led by local partners (universities, MPOs, non-profits). The USDOT Smart City awardee, Columbus, Ohio, is developing the Smart City Operating System as the core enabler of their portfolio of projects in the transportation and energy space moving forward, and is foreseen as a reference implementation for other smart city initiatives.
- Most urban data initiatives begin with incorporating existing mobility data gathered with traditional approaches as a foundation, and are envisioned to grow with new data from a variety of new sources such as sensors (some are experimenting with Internet of Things (IOT) approaches), crowd sourcing, probe vehicles, connected vehicle infrastructure and integrated visualization of data across partnering agencies.
- Transportation Network Companies (TNCs), such as Uber and Lyft, are on the radar for most cities with respect to the long-term impact on sustainability (e.g., congestion, emissions, equity, and/or land use impacts). TNC data availability has emerged as a critical data gap, perhaps the most urgent. Addressing this gap will benefit Smart City analyses, and also provide the base data to extend urban travel behavioral models. New primary data collection methods are emerging from the Urban Mobility Science pillar in collaboration with the Mobility Decision Science pillar, including data collection from driver, passenger, observational, and city/airport/parking revenues.
- The seven DOT Smart City Challenge finalist's modeling capacity (with specific technical focus on the urban travel demand process typically housed within Metropolitan Planning Organizations) with regards to the sophistication of individual trip behavior (activity based models versus four-step), and fidelity of network assignment (static versus dynamic assignment) and the extent of feedback between these components varied across the spectrum. Some cities, Columbus being the foremost example, are implementing state of the art models with the latest in activity based population and trip synthesis combined with a robust dynamic traffic assignment model. Others, such as Austin, rely on a more traditional four-step approach. However, the cities see the transportation demand model primarily as a rearward facing tool, informing of traditional mobility (vehicle based) and not dynamic enough to inform on quickly emerging mobility technology.
- The scenarios being explored with existing models span multiple topics, (technology, economic growth, land use, demographics) and are not homogenous across cities. The scenarios of interest are highly influenced by local context / priorities.
- The cycle length to renew urban transportation demand models (TDMs) averaged 8 to 10 years, as well as the associated local data collection cycles that support the TDMs. By their inherent nature, TDMs will continue to lag in their ability to reflect the influence of new technologies on the mobility system, particularly with rapidly adopted technologies such as TNCs (in agreement with the perception of cities.)
- The extent to which older modeling frameworks can be adapted to reflect the impact of ACES (both for mobility as well as energy) versus investing in more sophisticated, complex, and costly frameworks is unknown. Aspects of this identified knowledge gap are the subject of ongoing SMART Mobility projects moving into FY2018, in particular task 2.1.3 in cooperation with the city of Austin.
- The energy outputs from TDMs are produced typically from the EPA MOVES module that provides emissions estimates based on operating speed, volume of roadway segments. Some cities, in particular San Francisco, use the output from the TDM to report on sustainability goals related to VMT reduction. An enhanced energy estimation module that takes into account fleet mixture as exposed by state vehicle

registration data bases (in lieu of national or state averages), fuel consumption data, VMT and PMT (e.g., shared ridership estimates, and projections of future vehicle mix and extent of ridesharing will help align TDM practice with higher fidelity impact estimates.

A common theme both with respect to data and modeling was identifying appropriate energy and mobility metrics for smart city analysis. A ‘Quality of Mobility Metric’ reflecting this concept of the efficacy of the transportation network to connect citizens with the goods, services and employment that define a high quality of life is also a part of the Urban Science project portfolio (Task 2.1.2) moving forward in 2018.

Three initial papers and a report were developed in FY 2017. These are described in more detail below, including the abstract. Activities into FY2018 have already begun with several additional papers, and targeted publications in data and analysis of energy and mobility issues initially identified and explored in the curation deliverable.

2017 Papers:

A Convergence of Public-Private Benefits in Denver: Surveys and Analyses to Inform Urban Mobility-, Energy-, Infrastructure- and Behavior-Innovation, ITS World Congress Paper ID # AM-SP1340

Cities, public transit agencies, and new private ride-hailing services seek to understand emerging traveler dynamics, the shifting demographics of urban travelers, and new energy-efficient mobility opportunities. This includes exploring how new infrastructure investments, public and private mobility services, and smart-phone mobility apps are reshaping behaviors, demands (e.g., mobility-on-demand services), travel experiences and energy-efficient urban travel preferences. Currently, cities and metropolitan regions are providing and experimenting with many new mobility options, technologies, and personalized information services at the intersection of urban mobility, energy, and infrastructure systems (e.g., new commuter rail). To date, technology alone has not been able to crack the nut of “creating faster trip times, less congestion, safer streets, and cleaner air for its citizens through fewer cars on the road”. This paper focuses on this gap by offering new concepts and potential for integrated approaches. Accommodating more vehicle miles traveled in cities, without increases in person miles traveled (PMT), could be costly, generating: 1) tremendous demands for new infrastructure, land, road space, materials, and energy; 2) higher traffic fatality risks; and 3) worsening air quality. Therefore, this study focuses on reducing single occupancy vehicle use by enhancing integrated mobility, helping transit and ride-hailing increase occupancy in ways that also reduce energy use, and improve quality of life for urban travelers and communities. This study focuses on a survey of urban travelers in Denver, as a representative case study for city regions experiencing rapid growth, aging populations and infrastructure, increased urban sprawl, traffic-related delays, and inefficient energy use per PMT.

Exploring energy-efficient and sustainable urban mobility strategies: an initial framework to curate data/models, measure performance, and diffuse innovation, ITS World Congress Paper ID # AM-SP1339

Many cities across the United States seek to understand the maturity of data and models that are available to help manage challenges, opportunities, and uncertainties associated with the shifts in technologies, human behaviors and sustainable urban mobility strategies. One key question identified for smart city action planning is “how to best shape continuous improvements for urban populations at the intersection of mobility, energy, and quality of life?” With the emerging megatrends of urbanization (more than 70% of world population in cities by 2050), on-demand shared mobility, vehicle electrification, and automated vehicles, initial “urban science” studies to date have demonstrated the potential and need for maturing the related data and model ecosystems and on-going performance measurement across multiple urban system goals: e.g., from more mobility, clean and efficient energy use, accessibility and safety to less air pollution, traffic, and resource-intensive urban sprawl. To build on emerging literature and understand city responses to disruptive change, this initial study engages researchers and practitioners across four smart city finalists (Columbus, Denver, Austin and Portland) that competed in the U.S. Department of

Transportation (DOT) Smart City Challenge. The initial results emphasize the need for a suite of datasets and diverse analytical approaches that support U.S. Department of Energy (DOE)-relevant research with cities. Considering desirable energy and mobility outcomes as a first step to advancing smart city solutions strategies, we systematically review approaches of and shortcomings in four U.S. cities, and suggest improvements in three areas: measurement, modeling effectiveness of new mobility technologies, and data-driven governance.

Smart City Finalist Mobility Data on Trends in Commuting and Use of Ride-hailing: Exploring Potential for Shared Mobility-Transit Interplay to Inform Energy Savings, TRB 2018 Submission

This paper explores data trends across the seven US DOT smart city finalists, with emphasis on comparing travel modal split and commuting patterns. Commuter mode choice has energy usage impacts, as daily commuting habits significantly contribute to the transportation energy budgets of most Americans. According to American Community Survey estimates, approximately 86 percent of Americans use a car to get to work, and approximately 76 percent drive to work alone. There is thus significant room for improvement in the energy efficiency of daily commuting. The following key questions are identified for the analyses described in this study: 1) Do longstanding trends hold true with new emerging mobility as a service technology? Can we gain new observability on travel modes, commuting, and emerging transit-transportation network company data and their interplay? Understanding synergies and tradeoffs between transit utilization and transportation network company (TNC) utilization is of high interest, and can help to inform observability across cities on new alternative modes for daily commutes. With single occupancy vehicle (SOV) travel being more energy intensive than carpooling, public transportation, or shifts from ridehailing to ridesharing, this study explores key spatial opportunities for matching origins and destinations for commuting in selected cities. In-depth case studies of employee-origin data coupled with TNC data is utilized to explore such synergies. Spatially mapping the ‘hotspot’ areas for SOV commuters, carpool commuters, public transit commuters, and where TNC service drivers and users may align could yield important information to decision-makers on where to design and plan new energy efficient mobility upgrades.

The Evolving Maturity of Transportation Data and Models across Smart Cities, Draft NREL Technical Report

Through the use of emerging data platforms, new mobility technologies, and travel demand models, governments, researchers, industry, and communities can together improve the quality while maximizing the energy efficiency, equity, and safety of transportation services in their cities. As transportation may soon reach over 30% of U.S. energy consumption, and with urban areas representing an increasing proportion of U.S. population (>80% since 2010) (U.S. Census 2010), a critical need exists to engage in urban data science-informed approaches to enhancing mobility. This study explores how new approaches to transportation data and models are emerging to support data-driven and smart city mobility programs, projects, and policies. These approaches range from establishing an ‘integrated data exchange’ in Columbus, ‘data utility’ in Pittsburgh, a ‘PORTAL’ data archive in Portland, an enterprise data management system in Denver, a ‘one data system’ and ‘data rodeo’ in Austin, an award winning ‘Xaqt’ platform in Kansas City, to ‘DataSF’ in San Francisco. Most of these systems are being developed in parallel with multiple new data analysis tools, while regional metropolitan planning organizations (MPOs) continue to evolve travel demand models to help support planning, decisions, and infrastructure investments by taking into account emerging mobility technologies. Smart City initiatives in the United States are considering the many emerging and disruptive mobility services and technologies, with keen interests to leverage knowledge and research on the mobility benefits of automated, connected, electric, and shared mobility; and understanding the related energy, environmental, economic and societal impacts of these shifts. Building on this context and the U.S. Department of Transportation (DOT) Smart City Challenge, this paper curates the evolving data and modelling environments of the seven cities selected as challenge finalists, and their respective research and investment priorities. This effort includes stakeholder engagements with the seven Smart City finalists whose initiatives track and emanate from their respective

Smart City Challenge proposals. A major objective of this curation is to share lessons-learned from investments in data, analyses, modeling, and early-stage research across diverse cities that are all striving to implement Smart City programs. More specifically, the major focus of this paper is characterizing current urban data, mobility models, and their evolutions, as well as how these systems can help cities innovate at the intersection of mobility and energy.

Conclusions

In summary, the current state of urban data and mobility models along with city goals and priorities in the smart cities energy-mobility space were considered. City data infrastructure and mobility modeling capability were characterized according to their ability to support ongoing evolutions with emerging mobility technology related to vehicle automation, connectivity, efficiency & electrification, and sharing (ACES). The curation deliverable created the baseline foundational information in order to explore how these systems are evolving, and to help cities innovate at the intersection of mobility and energy. Overall key takeaways from data collection, analyses, and smart city stakeholder focus groups to date include an increased need to:

- Provide cross-city platforms to visualize city data and model environments as they transition and transform, in response to disruptive changes in mobility and cyber-physical infrastructure
- Harmonize approaches, both in data and modeling, by developing common methodologies to observe transitions in coupled urban mobility-energy impacts resulting from emerging mobility technology
- Address specific knowledge and data gaps as critical early-stage research; of particular need is to explore impacts, prepare for, and shape transitions in cities at the intersection of mobility and energy as mobility-as-a-service (MaaS) grows and proliferates.

Extending and enhancing urban transportation modeling and data environments to capture the short, mid, and long-term mobility benefits and energy efficiency associated with evolving city transport is critical to shape significant congestion, mobility, economic, affordability, accessibility, and resilience impacts.

While new technologies are enabling new data collection, modeling, and planning considerations, the research and science that can inform the future of cities needs to keep pace. Data/model integration, visualizations, and analytics will continue to emerge, and a goal of this initiative was to further enable city-driven knowledge through exchange and best practices via cross-city smart analysis such as this. This Smart city curation of data and models will continue in 2018 as a living document that can be periodically updated. The curation activity is intended to continue enabling efficient access to data for analyses and ongoing data streams from Smart City peer cities, to benchmark progress especially as it relates to smart city mobility pilots. With data on emerging transportation technologies identified as a key knowledge gap (perhaps the most important and urgent), tasks in the follow-on year target data collection initiative related to urban mobility as briefly described below.

- Transportation Network Companies (TNCs) impacts to mobility, parking, infrastructure, through their associated revenue streams is a leading indicator of mobility-as-a-service proliferation at the urban scale. TNC data is critical not only to measure existing impacts, but also a precursor of adoption of mobility service paradigm at scale when vehicle automation matures. Fiscal year 2018 data collection targets key mobility hubs associated primarily with airports, but can also extend to other mature intermodal transportation hubs, (e.g., downtowns, residential, and commercial districts), where revenue streams are closely accounted for. Revenue impacts (i.e., ‘following the money trail’) at prime shared mobility markets that charge access, ridership, and/or parking fees, allows for insights in travel behavior shifts, anticipate infrastructure impact, and ultimately energy impacts.
- Secondly, direct access and processing of state vehicle registration data bases is emerging as a key asset for research and enabling state and local informed decisions. Previously viewed primarily as a research data sets (and typically enabled through third party licensing) both SMART research activities and involvement of the technologist in city at Columbus have underscored the amplified need for such data at many levels, and for ongoing analysis and decision making. This effort aims to process data directly

from three or more states, in order to cost-effectively enable data access (while maintaining privacy) for SMART research and smart city activities.

- A third area explored, in collaboration with industry, is to develop useable new urban data that informs DOE and cities. An ongoing, industry-supported yearly survey initiative to gather data on citizen behavior, energy efficient mobility practices, adoption of MaaS at scale as well as AVs, EVs, and other emerging modes, would serve to measure and benchmark metrics that reflect the mobility, energy productivity, and economic vitality from a citizen's perspective for urban areas. An industry base for such an initiative would drive standards, and consistent practice.

This report on the curation of the seven DOT Smart City Challenge finalist's transportation data infrastructure and modeling capability encompasses first gathering of information about the city's priorities and motivations in the Smart City space, followed by a technical analysis of the data and model environments currently used in each finalist's city and lastly mapping those capabilities to the needs of mobility/energy innovations within Smart City initiatives to identify gaps and opportunities. A glimpse into how cities connect with mobility data and models will help explore current city planning and decision-making around emerging mobility transformations. A key finding is that each city prioritizes a robust data infrastructure to monitor and shape their decisions in mobility/energy systems, and to provide performance-based measures to assess progress toward their goals. Continued collaboration as relevant to energy-efficient mobility and key stakeholder questions, will remain critical to advancing energy efficient mobility systems across cities, regions, and nationally, and to support each city's priorities to secure economic growth, create new jobs, provide health care, ensure adequate and equitable access to food, housing and services through affordable, reliable, smart, resilient and modern 21st century U.S. transportation infrastructure.

Key Publications

1. A Convergence of Public-Private Benefits in Denver: Surveys and Analyses to Inform Urban Mobility-, Energy-, Infrastructure- and Behavior-Innovation, ITS World Congress Paper ID # AM-SP1340
2. Exploring energy-efficient and sustainable urban mobility strategies: an initial framework to curate data/models, measure performance, and diffuse innovation, ITS World Congress Paper ID # AM-SP1339
3. City Trends in Commuting and Use of Ride-hailing: Exploring Potential for Shared Mobility-Transit Interplay to Inform Energy Savings. TRB.
4. The Evolving Maturity of Transportation Data and Models across Smart Cities, Draft NREL Technical Report

V.2 Extending Urban Data and Modeling [Task 2.3.1]

Stanley E. Young, Principle Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway, MS 1625
Golden, CO 80401-3305
Phone: (303) 275-3283
E-mail: stanley.young@nrel.gov

Budhendra L. Bhaduri, Principal Investigator

Oak Ridge National Laboratory
One Bethel Valley Road
P.O. Box 2008 MS-6017
Oak Ridge, TN 37831-6017
Phone: (865) 241-9272
E-mail: bhaduribl@ornl.gov

Jane Macfarlane, Principal Investigator

Lawrence Berkeley National Laboratory
One Cyclotron Road
Berkeley, CA 94720
Phone: (510) 486-5498
E-mail: jfmacfarlane@lbl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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Project Introduction

Transportation planning for new infrastructure uses travel demand modeling methodologies developed over decades, fed by traveler survey data collected every five to 10 years. Originally developed to predict roadway usage to help guide future capital investment in highway capacity, travel demand modeling (TDM) has evolved over the decades to encompass ever widening concerns such as air pollution, transit, intelligent transportation systems, and active traffic management. Traffic assignment models originally developed to reflect the peak period of the day, now have the capacity to model traffic for any hour of the day. Similarly, trip models have also evolved. Moving from primarily journey to work travel patterns, to modern activity based models (ABMs) that create synthesized population and builds daily trips that span work, shopping, education, and recreation in completely linked trip plans.

These models are driven by a host of data. Survey data specific to an urban region typically is the foundation for revision of travel models. A regional survey provides a sample of local travel patterns to better customize trip generation tools. The travel models are then calibrated based on observed traffic volumes collected within the region.

By federal regulation, metropolitan planning organizations (MPOs) are required to create and maintain regional travel demand models, built and calibrated to a base year, incorporating region specific data through surveys, calibrated to observed traffic volumes, and then projected to future years based on land use scenarios, as well as planned infrastructure improvements. Federal regulations established this process to insure that

federal gas taxes were equitably distributed, and that the projects picked for funded provided benefit to region. These TDM models are the basic tools to explore the impacts of new transportation infrastructure be it roadways, transit service, or changes in land use to ease congestion. They are now being called upon to be the crystal ball by which we can estimate the impact of emerging mobility technologies such as automated vehicles, connected vehicles, shared mobility and vehicle electrification as they begin to roll out in urban regions around the country.

The primary focus of this task was to assess state of urban mobility data availability and modeling maturity to reflect the impacts of emerging mobility technologies, in particular vehicle automation and connectivity (CAVs), the sharing economy encompasses ride-sharing, car-sharing, ride-hailing and other emerging shared models, and vehicle efficiency/electrification. Many times this is abbreviated as ACES - automated, connected, efficient (or electric), and shared. TDM has, for the most part, been grounded using past experience to predict future roadway network dynamics. With the inclusion of ACES technologies, the fundamental issue is whether our TDM tools can be of value given the lack of any historical basis (experience and data collection) with the new technology, and what gaps exist in either data or modeling algorithms to make them viable for research and urban area future scenario analysis. Understanding of the current state of the practice, and the gaps between that practice and what is needed to forecast the impacts of ACES technology is essential to guide research and planning efforts.

Objectives

The objective was to assess state of urban mobility modeling maturity and capacity for SMART mobility assessment, identifying gaps in knowledge, data, and process which must be addressed to reflect the impact of ACES technology both for mobility, as well as the associated energy impacts. Realizing that the DOE is only a single player among many that work with TDMs, the process for identifying gaps needed to be inclusive of the group of larger industry expertise that included research and academia, commercial software and service providers, and practitioners from urban areas, all of which are dealing with the same issues with rapidly emerging mobility technology.

Approach

In order to solicit input from the broader industry, as well as develop a network of interested researchers across the industry, two workshops were hosted by the SMART Mobility Laboratory Consortium (SMLC). The first, hosted at Oak Ridge National Laboratory in November of 2016 focused on the modeling tools and methodologies, and the second hosted at the University of California at Berkeley in May of 2017 focused on the data and emerging data issues in the new economy. Both were successful in drawing a cross-section of researchers and practitioners, and in identifying the key issues and gaps for moving forward. A short recap of the proceedings and summary of findings are included in this annual progress report.

Mobility Modeling and Simulation Tools workshop

The SMART Mobility consortium of labs (SMLC) assembled a stakeholder workshop entitled: *SMART Mobility Modeling & Simulation Tools Practice, Challenges, and Future Directions* at Oak Ridge National

Lab on November 17 & 18, 2016. In addition to participation from laboratory researchers in SMART Mobility, representation at the workshop included industry consulting professionals, academic researchers, and transportation professional involved in day to day activities with modeling initiatives at the state, MPO, and city level. Over 65 industry professionals attended the 1.5 day workshop, sharing perspectives on the state of modeling practices to reflect the oncoming automated/connected/shared technologies that are transforming this space, as well as to discuss the ability of existing tools to quantify such impacts, identify key gaps in methods and data.



The workshop resulted in a summary of the invited speakers, edited by ORNL staff, and available at https://www.dropbox.com/sh/n4y9pqhiom5bf9q/AAAp04R_G3nk_ZQ5-JnnHWcNa?dl=0. The workshop closed with breakout sessions in which all participants were given opportunity to comment on critical issues and themes of the workshop. This feedback, sort of a Delphi process of experts, forms the basis for findings in the next section.

Designing Innovative Transportation Systems Solutions: Starting with the Data

The SMLC hosted a workshop to address the data issues associated with SMART Mobility on May 9-10 at University of California at Berkeley. The focus of this workshop was on the data needed to assess, analyze, and model future urban mobility, and scope was beyond just TDMs, including any initiatives to research and analyze emerging modes in mobility. The workshop discussed future scenarios that integrate emerging transportation solutions, their estimated population acceptance and behavioral impacts, the impact on mobility patterns and the consequent grid requirements, as well as energy use and dependence on fossil fuels. Specifically, this workshop directly addressed the necessary data that drives the analytics, modeling, and real-world testing needed to define and accelerate successful solutions of the future, and how increasingly that data resides in the private rather than the public sector.



The workshop results in a lessons-learned white paper discussing the findings at the data workshop: issues, gaps, and opportunities with data for SMART mobility, highlights of which are shared in the results section that follows. The workshop brought to bear the perspective that the data economy is fundamentally changing the landscape of research in this area. Research in which data is directly collected is giving way to methods to partner with existing parties that have access to critical data as by-products of commercial activities.

Results

The key outputs of the two workshops are summarized below. In addition to the knowledge gain, researcher and practitioner networking opportunities bringing together personnel both inside and outside of the department of energy was also a key outcome. Although the DOE is primarily interested in the energy impacts of ACES technology, not only are the methods and data are synonymous with the parallel mobility impacts, there is a growing acknowledgement and realization that future urban mobility must be approached from a multi-dimensional perspective that balances energy with mobility, productivity and quality of life, and that orthogonal research that just addresses a single dimension in isolation is insufficient with respect to urban science.

At both workshops representatives from academia, industry, and professional practice were present, providing a balanced perspective with respect to modeling tools and data. This resulted in confidently establishing a baseline understanding of the state of the industry. The USDOT Smart City finalists were also invited, and a majority of these cities were represented at both workshops. Similarly, the USDOT and its sphere of supporting research institutions were contributing participants at both workshops.

Key findings from the Mobility Modeling and Simulation Tools workshop

Listed below are a few major points. The overwhelming consensus of the participants, it should be noted, was that the primary gaps in practice had more to do with the enabling data than with the existing modeling frameworks. This is highlighted as the first take-away, but the emphasis on the importance cannot be understated.

Data on new systems and technologies (such as connected, automated, and shared mobility) is insufficient for model creation. Confidence in existing studies of ACES impact is extremely low primarily because the underlying models cannot be validated based on observed data. Modeling frameworks (Activity Based Models in conjunction with Dynamic Traffic Assignment) are generally acknowledged as adequate frameworks for ACES modeling, but the data to create the underlying probability distribution models which drive modern TMD frameworks was universally acknowledged as the primary inhibitor to progress. Investment by DOE in making such data available through demos, partnership with cities, and in collaboration with USDOT would be welcome by the modeling community.

Other takeaways and points of discussion included:

Energy consumption is already an output of existing TDM models, primarily using the EPA MOVES software. The transportation community relies on MOVES, and anticipates that as powertrains, EVs, and other aspect of the fleet evolve, that tools like MOVES will be available to integrate into TDMs (similar to existing MOVES software) to estimate energy consumption to a higher level of fidelity.

DOE TDM efforts based on agent based modeling or rapid modeling tools (such as in Polaris, MatSim, TUMS) are welcome, but is DOE is encouraged to stay connected to the transportation modeling community to understand needs and constraints of cities. Lessons learned from TRANSIMS about transferability and usability of results points toward the need for a continued industry wide consortium to leverage any investment in future modeling tools

The experts agreed that having a modeling approach that can be quickly initialized and scaled to different cities would be a great asset. Further, it is acknowledged that the lack of data availability is one of the biggest barriers for some of the models.

With unique computational resources of the national labs, it is timely to consider the integration of high-performance computing element in the TDM process. Recent development includes *CommuterSim*¹⁰ by ORNL researchers developed in the Repast-HPC platform and runs on TITAN.

Existing TDMs remain highway centric for the most part, and need to migrate to incorporate all modes, as well as all aspects of trips (door to door and not just garage to parking lot.) Full mobility models that incorporate all modes (pedestrian, parking, cycling, and transit networks), and associated human behavioral choice models will be critical with ACES technology with radically different mode choices being presented to the traveler. In addition to traditional modes, vehicle and ride sharing, ride-hailing (Uber and Lyft), empty vehicle recirculation, as well as fully automated and connected vehicles need to be integration.

Key Findings from *Designing Innovative Transportation Systems Solutions: Starting with the Data* workshop were synthesized from the workshop whitepaper currently in pre-publication, as well as notes from attendees.

The rapid pace of technology development is creating emerging trends in mobility that are driving change faster than our ability to model, design, and manage them. This could result in undesirable outcomes for our quality of life and radical impact on our environment. A common reflection among all participants at the workshop was the call for urgency in this domain, as the luxury of time as previously enjoyed for the planning and design of our highway and transit infrastructure, is quickly evaporating. We must begin now with the goal of facilitating the path forward and guiding it to a social optimum, rather than be led by technologies that may drive us to be continually creating a patchwork of decisions, actions, and investment that are reactionary with unintentional consequences, rather than strategic and purposeful.

Specifically with respect to the data, it is critically needed that drives our theory, policy, and models. With the technology revolution, pervasive use of devices is common across the world. Cell phones have grown well beyond the population growth. The Internet of Things (IoT) (including connected vehicles) is developing into a new data economy. Many of these devices are mobile and are collecting geospatial temporal data as part of their value proposition. These devices can provide data that can allow us to infer behaviors, inform and drive our models, and add significant insight into the mobility demands of our current populations.

The full range of topics bridged at the conference is beyond the scope of this summary. Some highlights are presented below in bulleted form. However the overwhelming theme, as mentioned above, is that this new mobility paradigm is upon us, and requisite urgency for meaningful data, analysis, and research to guide to optimum response.

Selected highlights:

- A new data economy is emerging, with a complexity that rivals that of our financial flows. The simplistic days of basic data collection and analysis are waning. More often than naught, critical data sets are created either directly or as a by-product of commercial activity, much of which is couple with smartphones, creating geo-spatially rich data sets that can be mined for a number of purposes, not the least of which is understanding the impacts of new mobility technologies. As with other shared-economies at scale, the data economy is quickly evolving with ‘middle-men’ or ‘wholesalers’ that

¹⁰ Aziz, H. M. A., Byung H. Park, April Morton, Robert N. Stewart, M. Hilliard, M. Maness, A high resolution agent-based model to support walk-bicycle infrastructure investment decisions: A case study with New York City, Transportation Research Part C: Emerging Technologies, Volume 86, January 2018, Pages 280-299, ISSN 0968-090X, <https://doi.org/10.1016/j.trc.2017.11.008>.

provide value added either with management, aggregation (or dis-aggregation), and privacy protection. This is a quickly developing world which DOE needs to be conversant to access data sets of relevance.

- High performance computing and machine learning are key enablers. High performance computing can play a critical role in the analysis of future generation transportation systems. Nationally there is a need for simulation of critical infrastructure such as transportation, energy, and water at scale. Many infrastructure problems have locational aspects that factor into the design and analysis of their functionality, requiring analytics of geospatial, and temporal data at scale. To simulate at scale will require partitioning the problem space on HPC resources. Machine learning systems on HPC will allow for large scale optimization algorithms to aid in the design of these complex systems.
- As a continuation of the main themes of the modeling and tools workshop, insufficiency of existing mobility data sources to enable agent-based modeling tools were discussed. The discussion evolved to smart and directed data collection, the ‘necessary and sufficient’ so to speak, to gain knowledge of key parameters required to accurately reflect new mobility paradigms.
- Closely related was the need to leverage and share data from ongoing demonstrations and early implementations. Many such activities ranging from major federal CV demonstrations, to CAVs testing grounds (as near San Diego), and numerous smaller automated electric shuttle demonstrations (as at Bishop Ranch) are on-going, and their data and lessons learned are critical in this rapidly evolving environment.
- Disagreement and debate on time horizon related to autonomous and automated features in vehicles continued, with industry promising functionality within five years, and credible research opinions estimating five decades. Regardless of the AV maturity cycles the needs, behavioral changes, and economic impacts of existing pressures (ride-hailing, car-sharing, lack of highway, funds, and escalating congestions and mobility disparity) on the urban mobility networks continue to prompt urgent research and response.
- The synergism connected, automated, electric, and shared was debated. Although each can theoretically continue to be developed and deployed independently, it is the intersection of these technologies that are causing significant disruption, and well as present significant opportunity – particularly for urban areas.
- Measuring human behavior response is emerging as key aspects of the data gap. Whereas traditional methods for vehicular and roadway impacts and influences are available (though quickly evolving) the human behavior aspects, and its evolution in response to new modes and services, will have the greatest impact on long term energy and productivity changes. Efficiently and effectively monitoring such behavioral response is a key leverage point for effective research.
- Lastly, an underlying theme of the urgency and relevance of automated, connected, efficient (electric) and shared mobility particularly on cities and urban areas was understood. This was reinforced by city representatives at the conference, and the numerous examples and discussions more relevant to city mobility, rather than farm-to-market, and interstate connectivity of past decades. As such the themes of the Smart City movement resonate highly with many of the DOE SMART initiative.

The full white paper will be published in early 2018.

Key Publications

1. *Designing for Mobility – A Call to Action*, whitepaper proceeding of the UC Berkeley / LBNL Big Data Meeting: Designing Innovative Transportation Systems Solutions Starting with the Data, Simons Institute, University of California, Berkeley, CA May 9–10, 2017, to be published 2018

V.3 Calibration of Activity-Based Transportation System Simulation Tools using High-Performance Computing [Task 2.3.2]

Dominik Karbowski, Principal Investigator

Argonne National Laboratory
9700 S Cass Avenue, Building 362
Argonne, IL 60439
Phone: (630) 252-5362
E-mail: dkarbowski@anl.gov

Vadim Sokolov, Principal Investigator

George Mason University
4400 University Drive
Fairfax, Virginia 22030
Phone: 703-993-4533
E-mail: vsokolov@gmu.edu

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$165,000

End Date: September 30, 2017
DOE share: \$165,000

Non-DOE share: \$0

Project Introduction

Transportation models are complex and stochastic processes that take years to develop and can cost millions of dollars. These models are highly sensitive to input variations and possess high dimensionality issues. Traditionally, any inaccuracies in the outputs of these simulators tend to be addressed ad-hoc by their developers. However, this is often limited to the beginning of a model lifetime as developers move on to other projects. New technology and modeling updates, as a result, tend to be rarely integrated and often lead to a decrease in the usefulness of the model and to a lack of confidence in results or, in some cases, expensive, obsolete models.

The goal of this research is to create an automated framework for calibrating a simulation model to produce more reliable forecasts without the need for manual code or calibration changes. This can allow for new types of datasets to be incorporated into older models and align outputs more closely with those observed in the field.

Furthermore, the increasing complexity of transportation computation modeling results in evaluation times of a single input set to range from many hours to days. In particular, the POLARIS model used as an example in the development of this framework can take up to a day to evaluate a single run. This computational constraint can potentially limit the scale and scope of calibration investigations which can result in large areas of sample space unexplored and sub-optimal decisions. So, in addition, the proposed framework will utilize high performance computation and machine learning techniques to minimize calibration time.

Objectives

- Build a framework for automated transportation system model calibration; such framework would compute the parameters of the model for a given city that make the simulation results match with a real-world dataset.

- Automate and speed-up the model building process, so that it is possible to build a new transportation model for a city or update an existing one with minimal user inputs.
- Provide better forecast reliability and certainty: thanks to the proposed framework, the transportation model will be easier to maintain and update with real-world data, therefore increasing the validity of simulation results for alternative mobility scenarios.
- Facilitate the development of energy-efficient mobility systems tailored to real-world situations.

Approach

We developed a computational framework that is built on two classes of components:

- Software libraries for efficient and robust execution and management of simulation jobs on high performance computing cluster;
- Optimization algorithms to explore input parameter spaces to find optimal solutions according to an objective specified by the modeler.

The framework implements three iterative stages: Evaluation, Integration, and Exploration.

Evaluation Stage using software libraries. New input recommendations obtained by the previous cycle's exploration stage require evaluation of the resulting model outputs. This is accomplished by running the queue of pending input sets concurrently through the simulator. Parallel instances of the code are created and each occurrence is provided with a unique input set to evaluate. HPC programs, such as Argonne's Swift-T framework, allows for coordinating worker units to run these simulator codes to maximize the available resources and time management.

Integration Stage using Optimization algorithms. The simulator to be calibrated is complex and mathematically intractable. Calibrating such model is considered particularly challenging because of costly, high dimensional relationships that are generally nonlinear and cannot be infinitely sampled. As a result, black-box methodologies, which assume to only know the inputs and outputs of a process, must be employed. Our framework uses a surrogate model which can be quickly evaluated to estimate the unknown relationship between the simulated results, $f(x)$, and observed outputs, y , at a given input set, x . A probability distribution, referred to as a Gaussian Process, over all potential linear and nonlinear functions representing this relationship is determined utilizing Bayes' theorem, which states that the posterior probability of a model, M , given a set of evidential data, is proportional to the likelihood of the evidence given the model multiplied by the prior probability of the model:

$$P(\text{Model}|\text{Evidence}) \propto P(\text{Evidence}|\text{Model})P(\text{Model})$$

Exploration stage using DOE and machine learning. Once the integration stage is complete, the exploration stage begins. This stage determines which samples should be evaluated in the next cycle to increase our understanding of the integration stage's probability distribution across functions. Several Design of Experiment methods exist for determining the next set of inputs for exploration of a sample space. However, the computational complexity of the transportation model to calibrate results in long and costly simulations for a single experiment alone. Particular attention must be therefore given to minimizing the number of samplings without compromising the final recommendation. A branch of machine learning techniques known as active learning specializes in addressing this constraint. These techniques are used to determine the optimal input sets that maximize the amount of information that can be gained by another evaluation stage. This is accomplished by maximizing a utility function which balances the exploration of unknown portions of the input sample space with the exploitation of known state space variabilities over the state space. In the field of statistics, these methods are also known as optimal experimental design. It should be noted at this framework does not aim to specify a single utility function to be used in all employed circumstances but to provide context behind

which active learning utilities should be used for specific calibration situations. Given the chosen utility function, this stage determines where to evaluate next. Depending upon the settings, this recommendation can range from a single input set to multiple sets.

Results

Prototype Framework

To test the HPC evaluation libraries and optimization algorithms we developed a lightweight transportation system model that can be executed in a few seconds. Using the model, we performed a sensitivity analysis of model outputs to inputs. We identified less influential input parameters. We empirically analyzed sensitivity of demand-related inputs to the travel time outputs. Overall, the lightweight framework allows to develop an intuition for appropriate surrogate models to approximate the POLARIS simulator. The transportation network used in the light-weight prototype as well as the results of the sensitivity analysis are shown in Figure V.3-1.

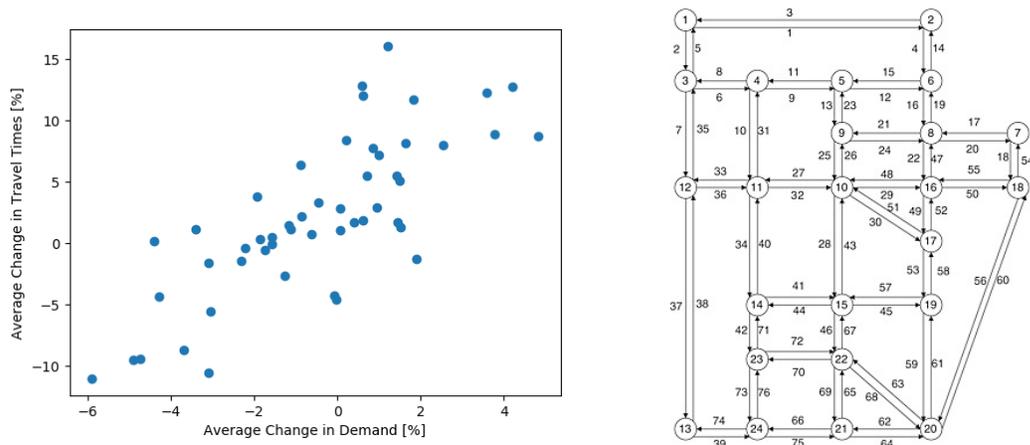


Figure V.3-1 - Sensitivity of travels times to changes in demand (left) and Sioux Falls network used for light-weight prototype model (right)

Dimensionality Reduction

The curse of dimensionality practically means that naïve exploration of input parameter spaces while searching for the best solution is impractical in dimensions larger than roughly twenty. One of the ways to reduce the dimensionality of the input vector is to hand pick the parameters to be explored. Though this approach can be efficient, it is not easily transferable from one model to another. Another widely applied technique uses **Principal Component Analysis** (PCA) to find linear combinations of input parameters that can be used to replace the original parameters. We applied the PCA to the origin-destination matrix from the Chicago model. The model has 2000 traffic analysis zones, which results in the accompanying OD matrix to have the size 2000 by 2000 or four million parameters needing to be optimized. Using PCA, we reduced dimensionality to $100 \times 2000 = 200$ thousand parameters, which is still a very high dimensionality (not low enough for efficient calibration), but only 40% variance can unfortunately be explained. Further research was required in this direction.

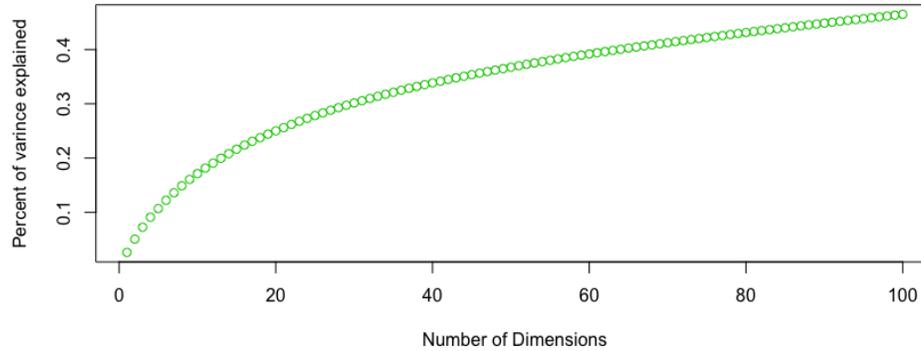


Figure V.3-2 - Scree plot that shows relation between subspace dimensionality and variance explained

To address the issue, we turned to the *active subspace* approach, which reduces the parameter dimensions of the surrogate model used to analyze a simulation by identifying and segregating the input dimensions into important, or active, and less-important, or inactive, directional categories. By identifying a reduced dimensional space, analysis methods that do not perform well in high dimensions, such as Gaussian surrogate techniques, could now be viable and explored. The primary difference between the Principal Component Analysis (PCA) method and the Active Subspace method centers around the criteria used to determine what eigenvalues are significant. PCA will choose the eigenvalues which, when summed, reach a pre-specified proportion of all eigenvalues. Active Subspace looks for the point in which a gap exists between eigenvalues. To the left are the active subspaces and to the right are the inactive subspaces.

Active subspace identifies, through the analysis of gradients and Eigen decomposition, linear combinations of inputs which significantly influence, on average, the output of the simulation when minor adjustments are made. The resulting eigenvalues of the decomposition are plotted on a log-scale and a ‘gap’ or space is looked for. These gaps indicate the defining line between active (left of the gap) and inactive (right of the gap) subspaces. If no gap can be found, compiling larger sets of eigenvalues or sampling more within the current eigenvalue framework in order to increase the eigenvalue accuracy is suggested.

We use Spearmin library to implement the Bayesian search and developed custom implementation of the active subspace construction. Figure V.3-3 below shows the results of the Bayesian search algorithms applied to a twenty dimension problem and compared with the search in two active subspace dimensions.

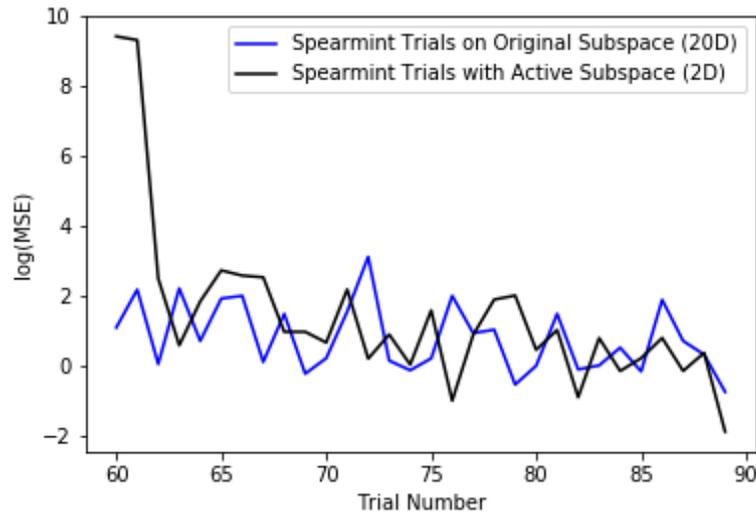


Figure V.3-3 - Results of demand matrix calibration using Bayesian optimization applied to original parameter space (blue line) and reduced dimensionality parameter space (black line). Dimensionality reduction was performed using active substance approach

Alternative Surrogate Models

Another approach to address the dimensionality problem is to choose a surrogate model of the transportation simulator that can effectively capture high dimensional integrations between the variables without limiting the types of relationships to consider. We developed a deep learning surrogate model to that end. We used results of sixty simulations to train the model which takes demand matrix as input and generates travel times as output. We then applied the model to predict the travel times given a demand matrix that has not been used to train the deep learner. Figure V.3-4 shows empirical performance of our deep learning surrogate model.

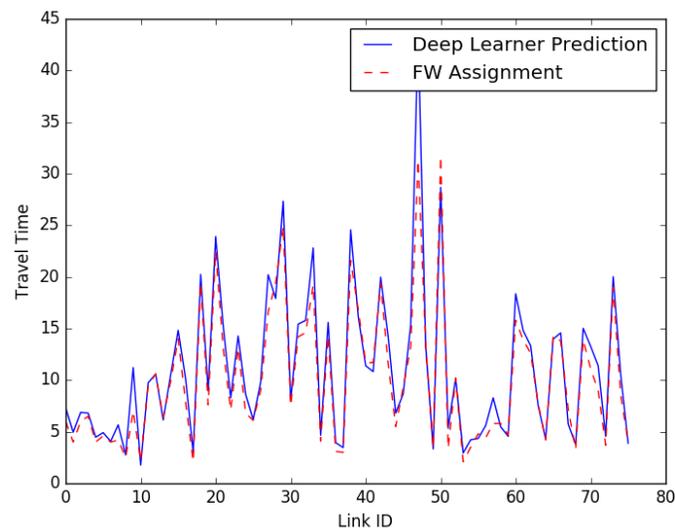


Figure V.3-4 - Comparison of simulator outputs (red dashed line) with the travel time values predicted by our deep learning surrogate model (solid blue line).

Based on the initial results, we believe that deep learning surrogate model is a viable approach; we will research further in this direction.

Conclusions

- Evaluation libraries based on the Argonne’s Swift-T framework have been developed for managing transportation simulation runs on high performance computers; this allows a large number of simulations in a reasonable time, which is required for effective calibration.
- A small size prototype transportation model has been developed and implemented; it represents the main roads of Sioux Falls; thanks to this light-weight model, it was possible to explore various solutions required for calibration.
- Several dimensionality reduction techniques have been developed and tested. The active subspace and deep learning approaches demonstrated promising results.
- An optimization model has been developed and applied to the prototype transportation model.

Key Publications

1. Laura Schultz, Vadim Sokolov, Josh Auld, Dominik Karbowski, Aymeric Rousseau, “Optimization to Fuse Large Scale Transportation Data Sets into Simulation Models”, invited presentation at INFORMS Annual Meeting 2017.

V.4 Develop and Extend Rapid Modeling Capacity of TUMS [Task 2.3.3]

H(Husain) M Abdul Aziz, Principal Investigator

Oak Ridge National Laboratory
Oak Ridge, TN 37830
Phone: (865) 241-3794
E-mail: azizh@ornl.gov

Budhendra L. Bhaduri, Principal Investigator

Oak Ridge National Laboratory
Oak Ridge, TN 37830
Phone: (865) 241-9722
E-mail: azizh@ornl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016	End Date: September 30, 2017	
Total Project Cost: \$115,000	DOE share: \$115,000	Non-DOE share: \$0

Project Introduction

This project demonstrates the application of density based data as a basis for rapid transportation model and simulation development. Toolbox for Urban Mobility Simulation (TUMS)¹¹, developed at ORNL, will use high-resolution population, travel demand modeling framework and data as input to run traffic simulation at the city scale. TUMS offers a set of tools for simulation-based studies of road traffic operations, urban planning, and extreme-event managements. Primary data sources for TUMS are weekly updated OpenStreetMap (OSM) data (transportation networks) and annually updated LandScan¹² data (population density and activity locations). TUMS comprises three main modules: data processing, network simulation, and visualization. TUMS is designed to accommodate different demand (activity generation) models and network simulation techniques. Further, TUMS has a visualization module to show traffic simulation for any geographic region in the world (<http://hippos.ornl.gov/tums/>).

Objectives

Key objectives for this project are: (a) To build traffic modeling capabilities for small-to-midsize cities in the US leveraging high-resolution population density data. Most small-to-mid size cities do not have a readily usable travel demand model that can be used to estimate the impact of connected and automated vehicles technologies in terms of energy and mobility, (b) To leverage ORNL product LandScan USA: high-resolution population data (temporal and spatial) and TUMS to build a rapid urban modeling platform.

Approach

To understand data needs and modeling formats, we have initiated discussion with the Mid-Ohio Regional Planning Commission (MORPC) at Columbus, Ohio. One key goal is the exploration and understanding the current state of transportation modeling practice by MORPC and preparing data needs for TUMS. The initial

¹¹ Lu, W., Liu, C., Thomas, N., Bhaduri, B. L., Han, L. D. (2014). A Global System for Transportation Simulation and Visualization in Emergency Evacuation Scenarios. Transportation Research Record, 1–17. <https://doi.org/10.3141/2529-05>

¹² Bhaduri, B., Bright, E., Coleman, P., & Urban, M. L. (2007). LandScan USA: A high-resolution geospatial and temporal modeling approach for population distribution and dynamics. GeoJournal, 69(1–2), 103–117. <https://doi.org/10.1007/s10708-007-9105-9>

stage, we have used the LandScan USA data to generate travel demand for Columbus, Ohio region and have used the TRANSIMS traffic engine to simulate the traffic. The road network is extracted from the open-source OpenStreetMap data. We are considering the Track-1 implementation of TRANSIMS within TUMS which requires origin-destination trip matrices input from an external travel demand model. Track-1 implementation in TRANSIMS is based on trip-based data. The basic input will be the trip tables and activity locations for the city of Columbus, Ohio.

Results

In FY 2017, we simulated the Columbus, OH region using our local LandScan USA database. The simulation is for demonstration purposes only. We use LandScan USA data (3 arc second) for population (90-m cells).



Figure V.4-1 - Distribution of population in the network with Google Satellite map layer. We have 111733 points for activity locations with population estimate. The size of the green circle represents the ambient population density in the cell that has been used to generate trip

TRANSIMS assigns activity locations along the streets. The number of activity locations per street is defined in a configuration file. TUMS assigned cell population to nearest activity location. TRANSIMS use these activity locations as the trip beginning and ending. Thus, each cell is assigned an entry link from that cell to the nearest node.

The visualization of the output can be found at <http://hippos.ornl.gov/tums/> From the drop-down menu, please select <Columbus5, OH>

Simulation details:

Study Area: 20 miles circle and the center is at the downtown, Columbus OH.

Original Network from OSM

Number of links: 118,394

Number of nodes: 107,336

External nodes (exit nodes, or destination nodes): 202

Original Cells from LandScanUSA (origin nodes): 111,773

Total population: 1,507,814

Generated Trips: Number of trips: 833,625 (60% of population. assume that 1.5 person per vehicle)

Number of Households: 833,635 (assume that one vehicle per household)

Simulation run time: 4:10:44, Number of trajectory points for 5 hours of simulation: 2.7B points

Please note that, this is a single simulation run for demonstration only.

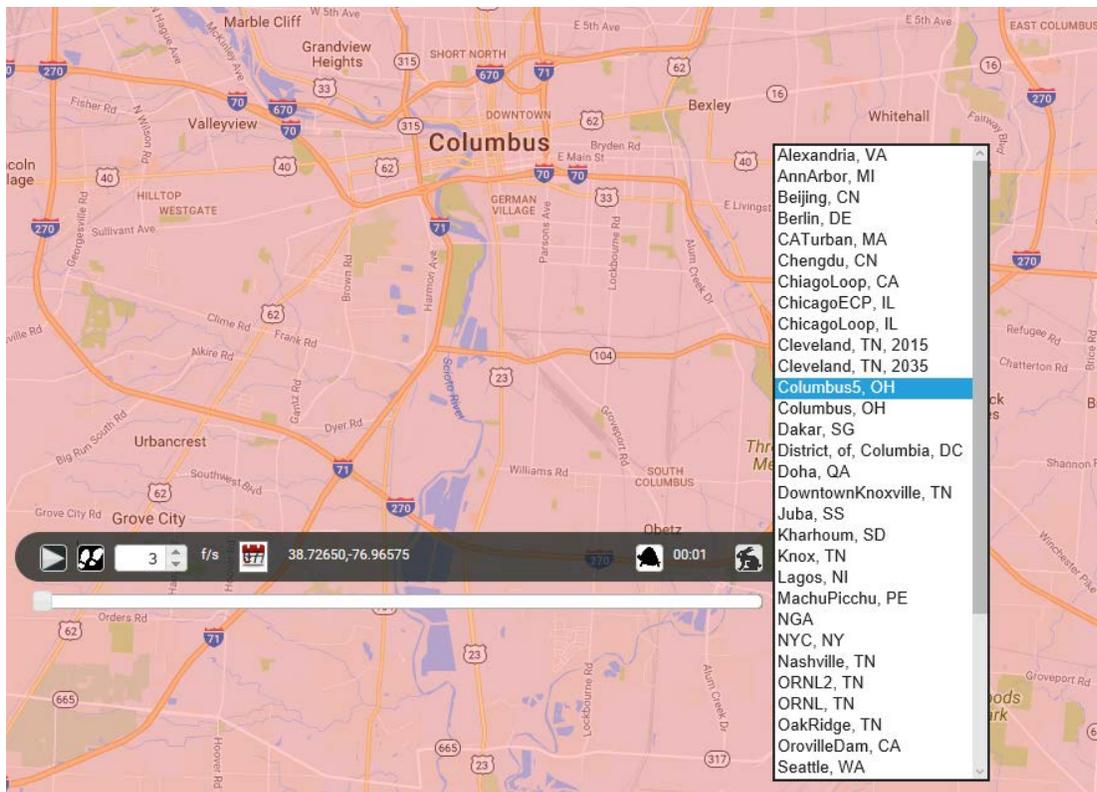


Figure V.4-2 - Selection of simulation city from TUMS web interface (<http://hippos.ornl.gov/tums/>)

In addition to the visualization, TUMS provides performance for each link in the network (text files and shapefile formats) that include: link speed, density, queue length, volume at a resolution set by the user (e.g., 5 minutes or 15 minutes).

Also, ORNL hosted a workshop on SMART Mobility Modeling & Simulation Tools (November 17-18, 2016). Insights gained from the workshop include: (a) data availability and veracity are major elements for the transportation models accommodating connected and automated vehicles, and (b) calibration and validation will require data fusion from different sources including legacy traffic count data, origin-destination trip matrices data, and cellphone data.

Conclusions

Our future tasks include a comparison of population density based approach with traditional 4-step or activity-based approached of traffic modeling. We will begin with the data from Columbus, Ohio. Further, we will explore calibration procedure for population density-based simulation that can be applied to create a locally adaptive travel demand—we will be able to run traffic simulation for any region in the US without direct access to legacy travel survey data.

Key Publications

1. Aziz, H M A., Liu, C., Bhaduri, B. L., (2017) Traffic Modeling of Columbus, Ohio using Population-Density based data through Toolbox for Urban Mobility Simulation (TUMS), DOE Internal Deliverable /ORNL Report (in preparation-future task)

V.5 Assessing Urban Impact: Automated Mobility Districts [Task 2.4]

Venu Garikapati, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
Phone: (303) 275-4784
E-mail: venu.garikapati@nrel.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016
Total Project Cost: \$720,000

End Date: September 30, 2019
DOE share: \$720,000

Non-DOE share: \$0

Project Introduction

Automated vehicles are increasingly being discussed as the basis for on-demand mobility services, introducing a new paradigm in which a fleet of automated vehicles displaces private automobiles for day-to-day travel in dense activity districts. This project examines such a concept to displace privately owned automobiles within a region containing dense activity generators (jobs, retail, entertainment, etc.), referred to as an automated mobility district (AMD). The goal of this project is to develop an AMD Simulation Toolkit that can quantify the mobility and energy benefits of on-demand automated electric shuttle services deployed in a confined geographic region. This framework is currently in development using open-source components, and will be exercised in 2018 with urban collaborative partners. During FY'17 this framework was prototyped using archives automated transit studies adaptable for energy and mobility metrics of interest for AMDs.

Objectives

- FY 2017
 - Develop initial modeling framework to quantify the energy and mobility benefits of AMDs
 - Initiate collaboration discussions with early AMD deployments
- FY 2018
 - Finalize AMD deployment partner
 - Collect travel survey data from deployment
 - Finalize modeling framework, develop a proof of concept AMD simulation toolkit to simulate intra-district travel behavior of AMDs
- FY 2019
 - Connect the AMDs with the larger regional travel demand model (for the chosen location)
 - Model inter-regional and boundary travel impacts of AMDs
 - Develop mobility and energy performance metrics for AMDs

Approach

- Perform extensive literature and practice search
- Develop a robust AMD modeling framework
- Prototype framework using existing transport datasets
- Translate the framework in to an open source (proof of concept) AMD simulation toolkit
- Collaborate with a real-world AMD deployment project
 - Started collaboration discussions with Greenville, SC, Houston University District, Jacksonville Downtown People Mover technology redevelopment effort, Babcock Ranch mixed use community development, and San Diego Military Base, among others.
- Collect travel survey & operational data from the chosen partnership
- Update the AMD simulation toolkit based on observations from real world data
- Produce case studies transferable to other AMD deployment sites

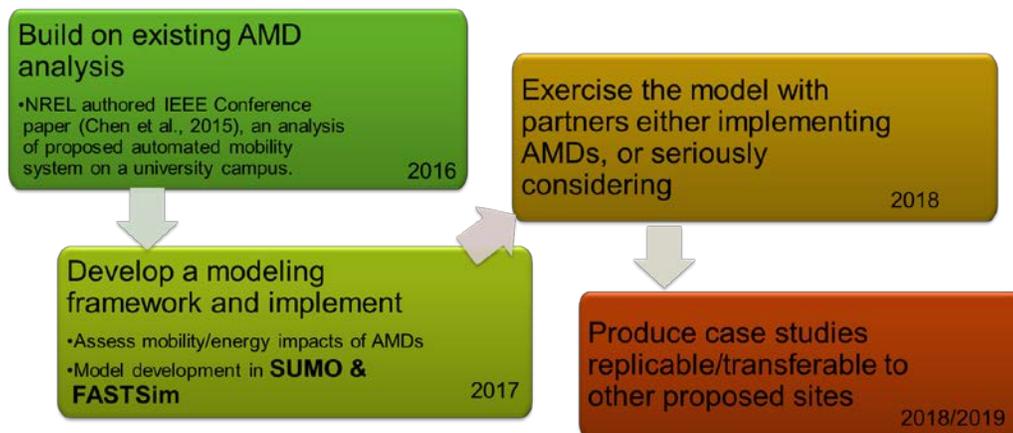


Figure V.5-1 - AMD Modeling Approach

Results

This initiative was seeded by exploration energy consequences using results from previous automated transit studies. A personal rapid transit (PRT) study for the campus of Kansas State University (KSU) was used as a surrogate to develop a framework to quantify the fuel consumption and energy impacts of a transit system comprised of AVs deployed on a college campus.

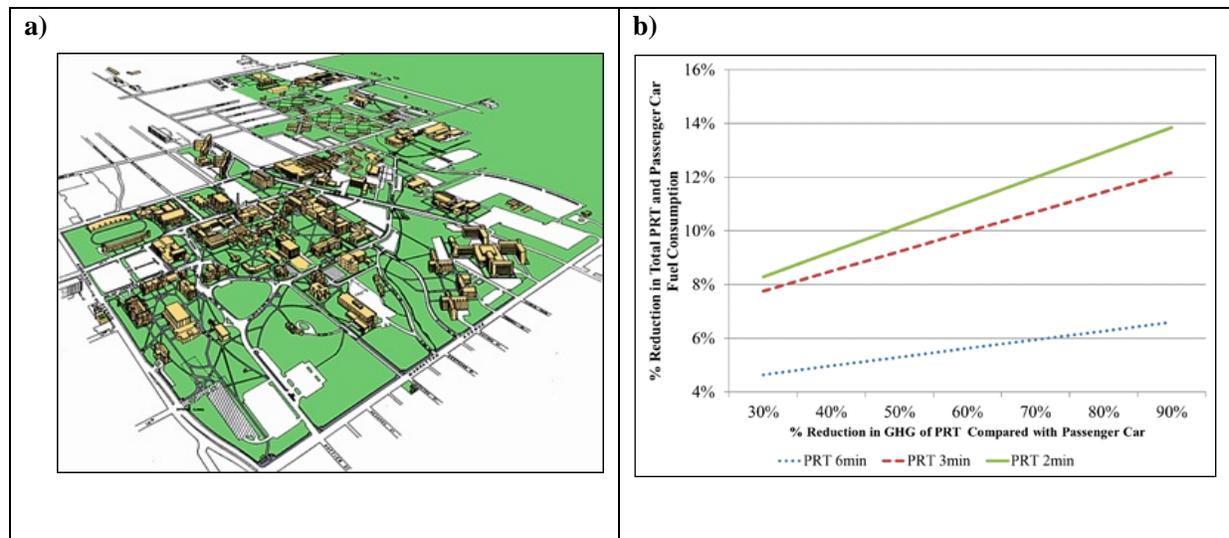


Figure V.5-2 - a) KSU Study Region; b) Fuel Consumption Benefits under different PRT Operational & Fuel Efficiency Scenarios

The key takeaways from the study include: i) Positive energy and emission results even though total VMT increased; ii) Reduction in vehicle fuel consumption by 4%-14% in the study area based only on resolving intra-campus mobility issues (shown Figure V.5-2 (b)); iii) Amount of energy and fuel consumption is primarily dependent on fleet characteristics of AMD, amount of ride sharing, and service frequency. The study concluded that even with the most conservative assumptions, the PRT system (analogous to an AMD in operation) showed positive energy benefits, and the energy framework proved pliable to build upon.

Major Accomplishments in FY 2017

- Organized an AMD modeling discussion session at the SMART Driving Cars summit in Princeton University, May 18-19, 2017
- Also organized a panel discussion at the Automated Vehicles Symposium (July 11-13, 2017, San Francisco) under the Public Transport and Shared Mobility track. The panel discussion focused on projects harnessing vehicle automation for public mobility to create Automated Mobility Districts.
- Greenville, SC has been recently awarded an Advanced Transportation and Congestion Management Technologies Deployment (ATCMTD) grant to deploy automated electric shuttles in 3 locations in Greenville County. The project team has established a Non-Disclosure Agreement (NDA) with the automated vehicle deployment partner in Greenville to facilitate data collection/transfer, and initiated a Memorandum of Understanding (MOU) with Greenville County to continue further engagement.
- The first year (FY 2017) of this project has focused mainly on engaging with partners initiating AMD deployments and developing a modeling framework for the development of an AMD Simulation Toolkit. The efforts in the first year led to the submission of a paper titled 'Initial assessment and modeling framework development for automated mobility districts' to ITS World Congress 2017. A brief summary of the paper is presented here.

AMD Concept Definition

The term "automated mobility district (AMD)" was introduced in 2016 to describe a campus-sized implementation of automated/connected vehicle technology to realize the full benefits of an automated vehicle (AV) mobility service within a confined region or district. As Silicon Valley and Detroit race to field fully automated vehicles, two approaches are taken. One approach is to incrementally introduce technology into the

consumer fleet until fully automated (and likely connected) operation is realized. This is the “something everywhere” approach in which ever-increasing control is given to the vehicle in successive model years. In the other approach, referred to as “everything somewhere,” fully capable automated mobility is deployed, but in a confined region. This latter approach allows developers greater control of the environment and less variance in implementation, thus minimizing risk. The AMD concept falls in this latter “everything somewhere” approach and is being realized in demonstration projects and some deployments across the United States and the world. AMDs interconnect all activities within a district, such as commercial (retail), entertainment and dining, and employment. Districts with sufficient concentrations of activity are candidates for such AV deployments. Activity centers may include jobs within a corporate campus, residences within a retirement community, classes and housing within an academic campus, or the many activities within a military installation. The common theme in these districts is connectivity among a group of buildings that encompass intense trip attractions—jobs, housing, commercial activities, etc.

The concept of an AMD is not new. High-value districts such as airports, amusement parks, and some campuses already restrict access by automobiles providing access to the property and interconnecting buildings with both non-automated (traditional buses, shuttles, and pedestrian walkways) and automated means (automated people movers [APMs], moving walkways, escalators, and elevators). However, the ability to implement an AMD using AV technology is a potential transformational element with today’s emerging AV technology. The use of AVs within a confined geographic area lowers the thresholds in terms of technology requirements and cost. A modern AMD system can be realized through a fleet of vehicles, envisioned as an automated taxi fleet controlled and dispatched within a limited geographic area. The system can use existing roadway infrastructure and provide personalized customer interaction through digital connectivity with the end user’s smart phone. A typical AMD system may have the following basic features:

- Fully automated and driverless vehicles. SAE level 5 vehicles capable of all safety-critical driving functions and able to monitor roadway conditions and to drive itself for an entire trip [1]. Such a design anticipates that the passenger will provide destination input, but is not expected to be available for vehicle control at any time during the trip.
- Service is confined to a geographic boundary that encompasses a relatively dense area of trip attractions, such as a campus area. This may be a medical, academic, or business park, or any other type of district. The geographic extent of the mobility system is limited, typically to 4 to 10 square miles.
- Mobility within the district is restricted to or dominated by the AMD. Within the district, access to end destinations is provided primarily by AV service or pedestrian access. Personal vehicles may or may not be strictly prohibited, but at a minimum they are highly discouraged, such as through policies controlling the availability and cost of parking. The district is designed to be most efficiently accessed by the AMD, although other forms may be permitted.
- Multi-modal access at the perimeter of the district. The AMD provides efficient opportunities for modal interface to the AMD, be it bus, light-rail, shuttles, car-sharing, bike-sharing, or other modes. This may include parking reserves for people to transfer from personal vehicles to the AMD to reach their final destinations [2].

Proposed Benefits of an AMD

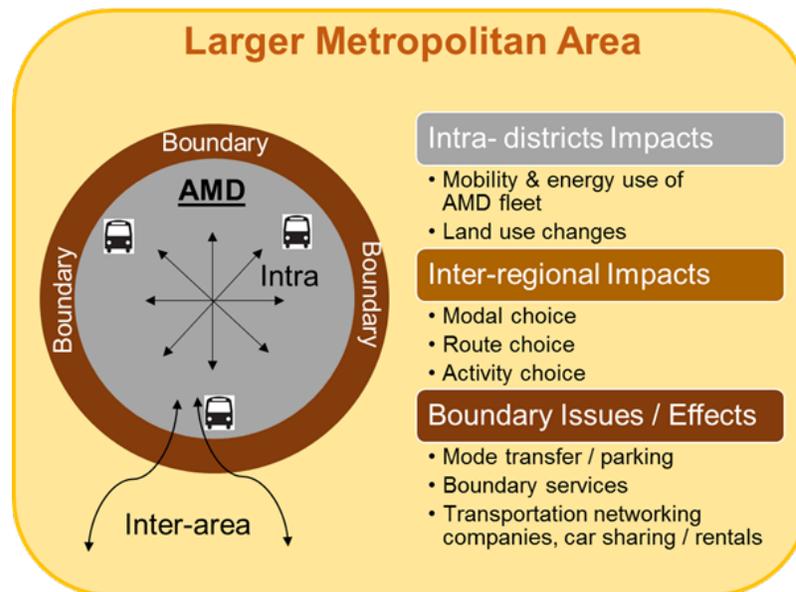


Figure V.5-3 - Analysis perspectives of AMD impacts within an urban area

An AV-based mobility district is postulated to address the challenges of dense activity districts, and even reduce their transportation energy impact. The impact of AMDs on mobility and energy use can be analyzed from intra-district, inter-district, and border issue perspectives. “Intra-district” is the extent to which quality of mobility and minimization of energy use is impacted for trips within the district. An “inter-district” or “inter-regional” perspective analyzes internal-to-external and external-to-internal mobility and associated energy use consequences, as well as possible trips between distinct AMDs. As the prevalence of AMDs within a metropolitan area increases, the opportunity to inter-connect the AMDs with shared and/or automated services further increase. Boundary issues/impacts result at the perimeter of the district and encompass modal transfer facilities, parking, and curb-side drop-off opportunities. The intra-district, inter-district, and boundary impacts are illustrated in Figure V.5-3 - Analysis perspectives of AMD impacts within an urban area.

Intra-district impacts, and effects are largely the result of eliminating vehicular trips and replacing them with AMD services. Mobility and energy impacts are internal to the district and include:

- Reduction (or possible full elimination) of personal automobile trips within the district and replacement by alternative modes including electric vehicle-based AV mobility
- Reduction in parking lots and structures internal to the district, freeing land for re-development and possible densification
- Reduction in vehicle–pedestrian congestion and conflicts, and associated safety benefits
- Land use and infrastructure changes that favor pedestrian activity, minimize road infrastructure and parking, and maximize curb-side drop-off/pickup
- Intra-district energy impacts can be directly observed and measured in deployed systems. Travel using personal automobiles is directly replaced by AVs, typically electric, on the roadways.

Inter-district impacts are those that affect the methods and patterns for accessing the district. Mobility and energy impacts arise from such issues as:

- Modal choice for accessing the AMD may change. A public transit or shared ride system (car-pool, transportation network company (TNC), etc.) may more efficiently aggregate riders to access the services across the AMD. Passengers traveling to any point in the district can disembark at the closest point of approach, allowing for greater opportunity of ride sharing or more efficient transit. Without the AMD, travelers to two different destinations within the district may not be able to effectively use the same shared mode
- Drivers' route selection may be altered and shortened. Rather than vie for parking close to the end destination, drivers only need to reach the boundary at the closest point of approach
- Activity choices may be altered to favor the well-connected services within a district. Analogous to transit-oriented-design in which services are concentrated on a well-served corridor, attracting greater patronage for businesses, an AMD likewise will provide access to multiple-services in a region, providing a single point at the perimeter to access a variety of services
- Inter-AMD (that is mobility between adjacent AMDs) trips can better aggregate travelers to provide more efficient shared ride options, be it transit, automated taxi, or casual carpooling. This latter affect is greatly unknown as no such paradigm currently exists. Multiple AMDs within an urban region may create a dynamic in which interlinkages between AMDs can be served with efficient, automated, shared, electric conveyance due to the high demand.

Boundary issues and effects encompass inter-modal transfer opportunities, as well as other commercial activity at the boundary due to convenient access. These include such aspects as:

- Locating car-share and bike-share assets at the boundary/perimeter to maximize usage potential for inter-district mobility
- Appropriate siting and capacity of parking reserves. Adequate parking available at all major points of approach will limit traffic due to drivers searching for parking, encouraging access to the AMD from the closest point of approach
- Inter-modal transfer facilities for transit. The AMD could substantially increase the catchment area for a regional transit facility or a shuttle system.

Challenges of Modeling AMDs

While AMDs are expected to achieve benefits with respect to reducing vehicle ownership, congestion, energy use and emissions from personal travel, rigorous AMD impact analysis is challenging as it must consider many modes of travel, intra- and inter-district impacts, and models of both the travel network and of consumer travel choices. Most previous AMD-related studies (in the vein of ATNs or automated taxis) were simulated based on hypothetical scenarios or assumed traffic parameters, such as traveler adoption rate, trip request rate, ride-sharing occupancy, fleet size, and vehicle operating speed. These critical parameters significantly affect the traffic simulation results of mobility, cost, energy use, and emissions impact of AMDs. Furthermore, most previous studies concentrate on only a single domain of impacts, be it simulating operations of the system to determine the number of AVs required, anticipated wait time, or consumer reaction in terms of anticipated ridership. Holistic approaches that capture the full scope of mobility shifts are scarce in literature. Obtaining objective and defensible traffic and ridership projections based on real field data remains one of the largest challenges of AMD studies because of limited field deployments of AVs. Generalized knowledge about traveler behavior within the AV domain is extremely sparse from previous limited automated vehicle deployments.

The impact of AMDs on travel behavior of individuals is still an unexplored territory. Will AMDs pave the way to more sustainable travel patterns? Will there be an increase in travel demand as people enjoy affordable transportation on-demand while increasing their productivity during travel? What is the impact of AMDs on short-term (mode choice) and long-term travel behavior such as vehicle ownership and use)? These questions need to be answered to accurately quantify the impacts of AMDs.

Conclusions

The following critical gaps were identified based on a review of exiting research in the realm of AMDs. Almost all of the existing AMD-related studies are simulation based and rely on numerous hypotheses and assumptions. While the results from existing studies provide a general idea of the impacts of AMDs on travel, none of the studies have been validated with actual field data. Future research should focus on models and frameworks informed from a full-scale field implementation of an AMD. Such an implementation is necessary to address the challenges identified above, and validate the assumptions made by previous studies. Questions pertaining to adoption rates; induced travel demand; operational attributes (frequency, fleet, and ridership); and energy/emission impacts of AMDs can be answered with certainty only after the users experience AMDs first-hand.

Building on the comprehensive literature review, and model framework development carried out in FY 2017, the modeling efforts for the next fiscal year will focus on:

- Developing a proof of concept AMD Simulation Toolkit
- Collecting travel survey and vehicle operational data from a real-world AMD deployment
- Augmenting the modeling components of the toolkit with data from real world AMD deployments.

Key Publications and Presentations

1. Y. Chen, S. Young, J. Gonder, X. Qi (2015). Estimate of Fuel Consumption and GHG Emission Impact on an Automated Mobility District. The 4th International Conference on Connected Vehicles & Expo (ICCVE 2015), Shenzhen, China, Oct. 23-25, 2015.
2. S. Young, Y. Hou, V. Garikapati, Y. Chen, L. Zhu (2017). Initial Assessment and Modeling Framework Development for Automated Mobility Districts. In Proceedings of the ITS World Congress 2017, Montreal, Canada, October 29 – November 2, 2017.
3. J. Sperling, V. Garikapati, S. Young, Y. Hou, A. Duvall (2017). Automated Mobility Districts and Net-Zero Energy Campuses: A Convergence of Resource-Efficient and Resilient Systems. Presented at the 2017 Defense Innovation Summit, Tampa, Florida, October 3-5, 2017.
4. L. Zhu, V. Garikapati, Y. Chen, Y. Hou, H. M. Abdul-Aziz, S. Young (2018, In Preparation). Quantifying the Mobility and Energy Benefits of Automated Mobility Districts Using Microscopic Traffic Simulation. Selected for presentation at the 2018 ASCE International Conference on Transportation & Development. Pittsburgh, Pennsylvania, July 15–18, 2018.

References

1. SAE International (2016). SAE J3016: Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems. SAE International. Available from: https://www.sae.org/misc/pdfs/automated_driving.pdf.
2. Y. Chen, S. Young, J. Gonder, X. Qi (2015). Estimate of Fuel Consumption and GHG Emission Impact on an Automated Mobility District. The 4th International Conference on Connected Vehicles & Expo (ICCVE 2015), Shenzhen, China, Oct. 23-25, 2015.

V.6 Role and Potential of Signaling Infrastructure [Task 4.0]

H(Husain) M Abdul Aziz, Principal Investigator

Oak Ridge National Laboratory
Oak Ridge, TN 37830
Phone: (865) 241-3794
E-mail: azizh@ornl.gov

Hong Wang, Principal Investigator

Pacific Northwest National Laboratory
Richland, WA 99354
Phone: (509) 375-6755
E-mail: hong.wang@pnl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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DOE Share: \$270,000

Non DOE Share: \$0

Project Introduction

Connected automation in transportation systems promises substantial benefits for reducing traffic crashes, improving mobility and accessibility, and minimizing energy consumption. Extensive deployments of connected and automated vehicle (CAV) technology over the next decades are anticipated and cities globally - from Austin, Nashville, Los Angeles, Columbus, Ann Arbor, Tampa, Pittsburgh, New York City, Denver, San Francisco and Boston in the United States; to Singapore; Gothenburg, Sweden; La Rochelle, France; Lausanne, Switzerland; Helsinki, Finland; London, England, Sao Paulo, Brazil, Tel Aviv Israel, Buenos Aires, Argentina, Paris, France, globally - are making efforts to plan and prepare for this transition. CAVs not only offer opportunities to improve the transportation, they also pose new challenges for optimal leveraging vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X) technology. This project explores the role of robust control infrastructure (signals and sensors) for heterogeneous traffic--a mix of CAVs and human drivers and aims to develop control algorithm with the objective ensuring minimal energy, maximum mobility future. The quality of vehicle flow in urban areas (as well as its energy efficiency) is dictated more by intersection control than by vehicle drivetrains and fuels. Our goal is to get answers to the questions including: (a) How will traffic signals and sensors shape command and control infrastructure to improve SMART mobility? (b) What is the potential gains--mobility and energy--from optimal sensing and control, increased observability from CAVs and improved sensor technology?

Objectives

Task 4.0 aims to investigate the needs and role of the traffic signal infrastructure system that includes sensors, roadside equipment, control device, and control schemes in a connected and automated environment. The focus is on a robust signal infrastructure system that can operate in a mixed fleet of connected and automated vehicles and human drivers and the potential system level gain in safety, mobility, and energy. The overall objectives are: (a) to investigate the transition and impact of traffic signal systems in a connected environment focusing on mobility, energy, and level of service, and (b) to develop robust signal control schemes leveraging connected and automated vehicle technologies--maximizing mobility with minimal energy. The specific objectives for FY 2017 (October 2016--September 2017) are: (a) to conduct a comprehensive synthesis study on existing signal infrastructure, (b) to engage collaboration partners for case studies and data needs, and (c) to

identify the future approaches to designing signal control algorithms accounting for data, communication, and transition in both vehicular and infrastructure technologies.

Approach

For the synthesis study, we focus on existing signal infrastructure components and the its transition to the connected and automated intersection environment, review of existing control schemes and future signal control applications that assume presence of Connected and Automated vehicles (CAVs), and deployment cost of CAV based signal infrastructure and control system. Further, we explored the signal control applications in pilot studies and Smart City proposals, and the lessons learned from US DOT Connected Vehicle Pooled fund project, and MMITSS (Multi Modal Intelligent Traffic Signal System) testbeds in Arizona and California. The publicly available NG-Sim datasets for arterials: Lankershim Boulevard Los Angeles, CA and Peachtree arterial in Atlanta, GA will be used as testbeds for control algorithm development in FY 2018-19. In addition, we have planned to collaborate with Iowa State University and University of Tennessee-Knoxville.

Results

Synthesis study on signal infrastructure and control:

Our synthesis study explores the current state of signal control algorithms and infrastructure, reports the completed and newly proposed CV/CAV deployment studies regarding signal control schemes, reviews the deployment costs for CAV/AV signal infrastructure, and concludes with a discussion on the opportunities such as detector free signal control schemes and dynamic performance management for intersections, and challenges such as dependency on market adaptation and the need to build a fault-tolerant signal system deployment in a CAV/CV environment. The study will serve as an initial critical assessment of existing signal control infrastructure (devices, control instruments, and firmware) and control schemes (actuated, adaptive, and coordinated-green wave). Also, the report will help to identify the future needs for the signal infrastructure to act as the ‘nervous system’ for urban transportation networks, providing not only signaling, but also observability, surveillance, and measurement capabilities. Key findings include:

A. Transition in infrastructure and algorithms:

The following Figure V.6-1 - Caption Transitions in signal infrastructure and control algorithms in CAV/CV environment shows the transition pattern. Transitions will happen in the automotive and communications technology as well as in the infrastructure including CV/CAV enabled intersections and possibly smart intersections without physical traffic lights. As communication capabilities advance, it is possible to design and implement control algorithms that can leverage the V2V, V2I, V2X and I2I and the data available in real time. We also anticipate these transitions will not happen in a linear manner and many uncertainties will be unveiled as we progress. Nevertheless, the automotive industries and the transportation infrastructure managing entities should prepare for the transition and cooperate to reach a minimal energy-maximum mobility future.

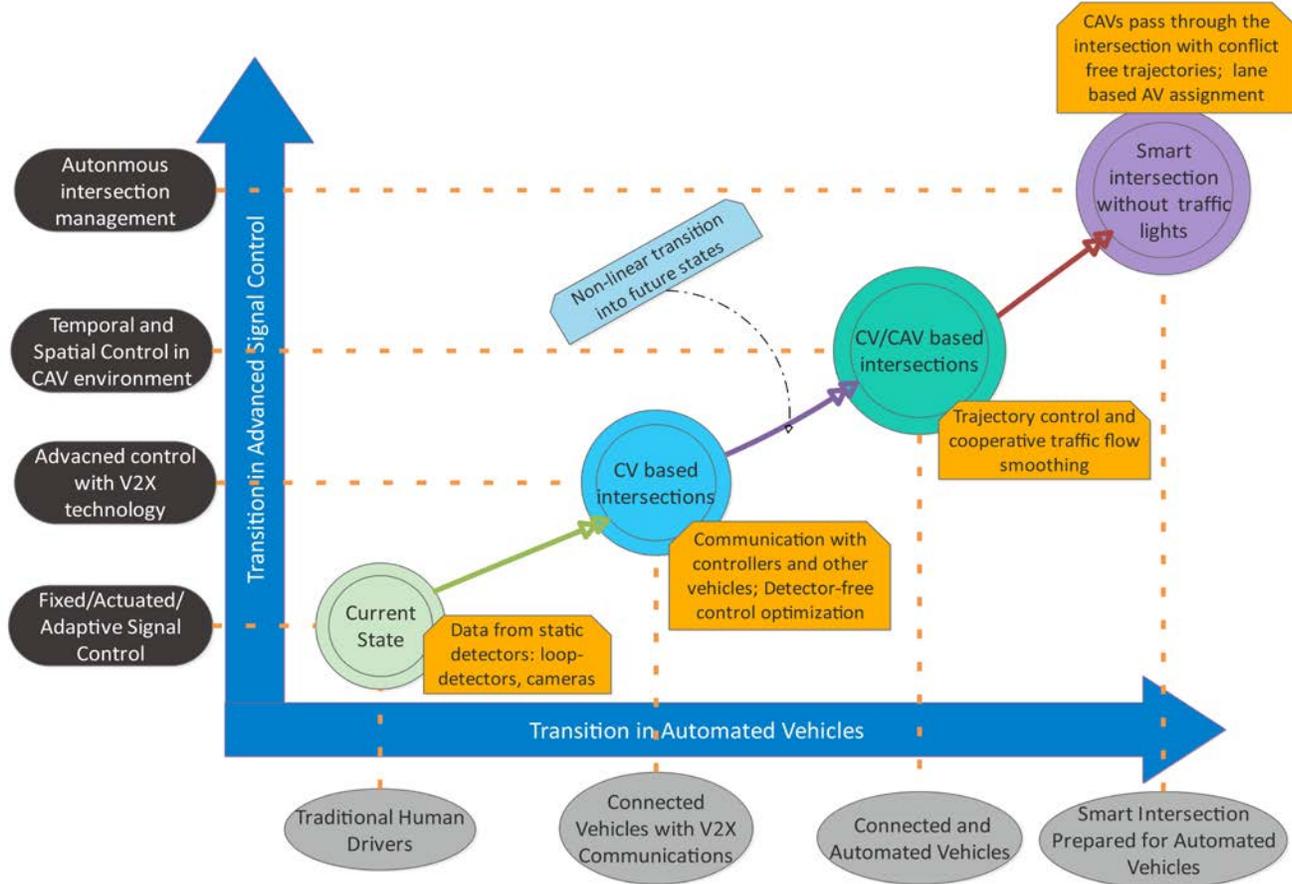


Figure V.6-1 - Caption Transitions in signal infrastructure and control algorithms in CAV/CV environment

(Source: Aziz, H. M. A, Hong Wang, Stan Young, Joshua Sperling, and John Beck. 2017. "Synthesis Study on Transitions in Signal Infrastructure and Control Algorithms for Connected and Automated Transportation". United States. doi:10.2172/1366412. [http://www.osti.gov/scitech/servlets/purl/1366412.](http://www.osti.gov/scitech/servlets/purl/1366412))

B. Detector-free signal control algorithm implementation

CAV environment offers a detector free option to optimize traffic signal. The CAVs will act as mobile detectors in the system and exchange data with the signal controllers that can be used to develop control schemes. Detector free performance assessment based on vehicle probe data provided by traffic industry is increasing visibility into existing signal control systems. HRCD, re-identification data, and travel time data derived from probe vehicle data are beginning to provide system-wide observability similar to that anticipate from CV/CAVs. Though not anticipated for real-time control input, the proliferation of these approaches provides significant improvement to established signal infrastructure, as well points toward statistical control methodologies for real-time control.

C. Dynamic intersection performance management

CAVs can be integrated with a central database, and the data can be used for performance management of the signalized intersection at the network level (Goodall et al., 2013). This offers an integrated system of signalized intersection monitoring and maintenance in real time. Further, the data-driven system can be coupled with autonomous intersection management system. If CAVs have powerful onboard computing power, we may not need traffic signal systems at all in road junctions as CAVs can optimize their movements

via communicating with other CAVs in the area and can thus have the ability to automatically pass through road junctions effectively.

D. Fault tolerance and resistance to cyber attacks

CV/CAV environment requires a highly reliable onboard computing and communication, and the system needs to be made fault tolerant if an unexpected fault occurs in the system. In this regard, concepts such as collaborative fault tolerant control at vehicle level should, therefore, be used so that if one CAV has a fault other CAVs can control their movements in a fault tolerant way to ensure a safe movement. Also, cybersecurity is another important aspect in CV/CAV environment. It is important to secure the privacy of the users and secured data exchange CV/CAV environment. The CAVs are supercomputers and if compromised can cause significant damage on a large scale. Under the NCHRP program, a primer on cybersecurity for surface transportation has recently published. The aim is to provide transportation agencies with cybersecurity concepts, guidelines, fundamental strategic, management, and planning information associated with cybersecurity and its applicability in CV/CAV environment.

Networked traffic flow optimization through stochastic distribution control:

Networked traffic flow is a common scenario for urban transportation, where the distribution of vehicle queues either at controlled intersections or highway segments reflect the smoothness of the traffic flow in the network. At signalized intersections, the traffic queues are controlled by traffic signal control settings and effective traffic lights control would realize both smooth traffic flow and minimize fuel consumption. A major challenge with such a complex traffic system is the operational quality - that is how a uniform traffic flow distribution can be maintained in the networked traffic flow area with minimum energy consumption such as gas and electricity. In this context, the traffic system is a large-scale multivariable stochastic distribution control system because the traffic flows are randomly distributed in the network where the number of the vehicles entering a road is stochastic. At present, there is limited literature on the real-time control of stochastic distributions of traffic queues in the networked traffic flow area. According to (Wang, Aziz and Young, 2017), stochastic distribution control can be used to develop distributed traffic flow control to make the probability density functions (PDFs) of the traffic queueing length in the network to approach narrowly uniform distribution. This would reflect a smooth traffic flow and subsequently minimizes the energy consumptions.

Findings:

We performed a preliminary investigation on the modeling and control framework in the context of an urban network of signalized intersections. In specific, we developed a recursive input-output traffic queueing models. The queue formation can be modeled as a stochastic process where the number of vehicles entering each intersection is a random number. Further, we proposed a preliminary B-Spline stochastic model for a one-way single-lane corridor traffic system based on the theory of stochastic distribution control. It has been shown that the developed stochastic model would provide the optimal probability density function (PDF) of the traffic queueing length as a dynamic function of the traffic signal setting parameters. Based upon such a stochastic distribution model, we have proposed a preliminary closed-loop framework on stochastic distribution control for the traffic queueing system to make the traffic queueing length PDF follow a target PDF that potentially realizes the smooth traffic flow distribution in a concerned corridor.

Conclusions

In FY 2017, we explored control algorithms and infrastructure needs in potential connected and automated environment relevant to traffic signal control settings. The synthesis study will serve as an initial critical assessment of existing signal control infrastructure (devices, control instruments, and firmware) and control schemes (actuated, adaptive, and coordinated-green wave). Also, the report will help to identify the future needs for the signal infrastructure to act as the 'nervous system' for urban transportation networks, providing not only signaling, but also observability, surveillance, and measurement capacity. The discussion of the opportunities space includes network optimization and control theory perspectives, and the current states of observability for key system parameters (what can be detected, how frequently can it be reported) as well as controllability of dynamic parameters (this includes adjusting not only the signal phase and timing, but also the

ability to alter vehicle trajectories through information or direct control). The perspective of observability and controllability of the dynamic systems provides an appropriate lens to discuss future directions as CAV/CV become more prevalent in the future. Further, the network flow control approach provides an initial recursive input-output traffic queue model along with the potential stochastic distribution control approach. This would take the timing of red, green and yellow signals as the control input and produces the queue length distribution as the output for traffic flow corridor by considering a number of vehicles entered and left the signaled corridor as both deterministic and stochastic processes.

For FY 2018, we planned to develop and execute control algorithm with mobility and energy objectives. Two major directions will be pursued: (a) reinforcement learning based control algorithm with multi-reward structure, and (b) stochastic control optimization of traffic flows at the network level.

Key Publications

1. Aziz, H. M. A., Hong Wang, Stan Young, Joshua Sperling, and John Beck. 2017. "Synthesis Study on Transitions in Signal Infrastructure and Control Algorithms for Connected and Automated Transportation". United States. doi:10.2172/1366412. <http://www.osti.gov/scitech/servlets/purl/1366412>
2. Wang, Hong, H M A. Aziz, Stanley E. Young, Sagar Patil. Control of Networked Traffic Flow Distribution - A Stochastic Distribution System Perspective. International Conference on Internet of Things and Machine Learning, Liverpool City, United Kingdom (October 17--18, 2017)
3. Aziz, H. M. A., Wang, H., Young, S., Sperling, J., & Bhaduri, B. (2017). Opportunities and Challenges in Traffic Signal Operations and Infrastructure Deployment in the Era of Connected and Automated Vehicles. In ITE/CITE 2017 conference, Annual meeting of the Institute of Transportation Engineers. Toronto. July 2017.

VI. Core Modeling, Simulation, and Evaluation

VI.1 Autonomie for MBSE Workflows

Phillip Sharer, Principal Investigator

Argonne National Laboratory
9700 S Cass Ave, Bldg 362
Argonne, IL 60439
Phone: (630) 252-9739
E-mail: psharer@anl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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Total Project Cost: \$500,000

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DOE share: \$500,000

Non-DOE share: \$0

Project Introduction

Autonomie is a plug-and-play powertrain and vehicle model architecture and development environment that supports the rapid evaluation of new powertrain/propulsion technologies to improve fuel economy through virtual design and analysis in a math-based simulation environment. Autonomie has an open architecture to support the rapid integration and analysis of powertrain/propulsion systems and technologies. This architecture allows rapid technology sorting and evaluation of fuel economy under dynamic/transient testing conditions.

To better support the U.S. Department of Energy (DOE) and its user community, several new features have been implemented in Autonomie. Some of the most significant accomplishments are described in this report.

Objectives

- Enhance and maintain Autonomie as needed to support the U.S. Department of Energy (DOE) and the user community
- Enhance Autonomie to expand its model-based system engineering scope
- Continue to enhance Autonomie to support DOE and technology transfer

Approach

There are always more ideas for new Autonomie features and enhancements than time to implement them. Feedback on which items to prioritize and include is collected in several ways.

First, users of Autonomie register suggestions for improving the software or models by email, in person, or through our online issue-tracking system at www.Autonomie.net. Second, direct interaction with partners and sponsors while working on shared projects contributes to collecting new requirements. Finally, DOE studies often drive the improvement of existing capabilities and/or the development of new ones.

Model Based System Engineering (MBSE) enhancements focused on longer-term strategies for the future of vehicle modeling and simulation. One strategy such strategy is the seamless integration of parallelization in workflows to enable effortless multicore computing. Another strategy was the integration of tools that, themselves, integrate tools, thereby increasing the breadth of the Autonomie ecosystem.

Results

Overview Accomplishments

- User Interface Enhancements
 - Released REV15 Service Pack 2
- Model Based System Engineering (MBSE) Enhancements
 - Released AMBER/Autonomie Alpha to Ford and GM for user feedback
 - Invented a way to select different workflows in Autonomie

REV15 Service Pack 2 was released

This service pack is an incremental update of current Autonomie and has several patches and numerous usability enhancements, which were chosen, based on user feedback. They are as follows:

Major User Interface Enhancements

- A Quick Import was added to Autonomie to allow users to import models and calibration files in one click without having to go through a separate dialog.
- Plot Templates appends plots instead of replacing current plots

Simulation Engine Enhancements

- New unit conversion class for converting measurements from one unit to another. This new units class is compatible with AMBER.
- Created a way to extract the vpc and all low controllers and build them all in the same diagram for export. (Requested by Toyota North America)

Over 92 other Bug fixes and Usability Enhancements were made

Model Based System Engineering (MBSE) Enhancements

Expanding the Autonomie Workflow Framework and Adding New Workflows

The concept of workflows is part of the design philosophy of Autonomie, and Autonomie has had great success in supporting user-defined workflows for a single vehicle. Under MBSE, many workflows exist, such as model verification and validation, Design of Failure Modes Analysis (DFMEA) analysis, vehicle validation and correlation, test data quality assurance, system based hardware-in-the-loop, system based software-in-the-loop, system based model-in-the-loop, large-scale study, and large-scale data analysis. Numerous OEMs and even other government entities have used these workflows and would benefit if they were supported in Autonomie. This project addresses these additional workflows by modifying the framework of Autonomie to support customized workflows that do not directly involve loading a single vehicle and running a simulation. Before addressing these other workflows, compatibility with the current workflow must be maintained and demonstrated. This new framework is referred to as the *Advanced Model Based Engineering Resource* or **AMBER**.

Figure VI.1-1 shows that AMBER provides a platform on which tools can be integrated and enabled to communicate with each other. Novel analyses are now possible by combining multiple tools into the same workflow. Combining POLARIS with Autonomie or RoadRunner with SVTrip now becomes a possibility. This new flexible architecture is designed to enable OEMS to add their own workflows based on their own in house tools.

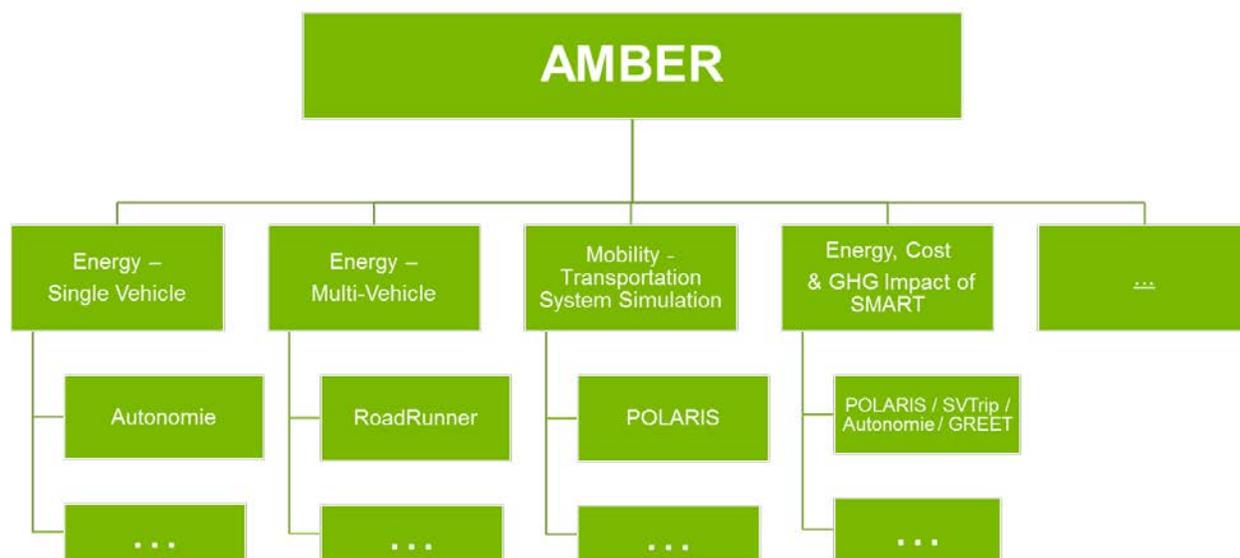


Figure VI.1-1 - Applications Based on AMBER

The user begins by choosing the MBSE workflow that matches their requirements. Workflows are divided into different categories. The two main categories are Developer and User. The workflows implemented this fiscal year are:

1. Smart Mobility (User Workflow)
2. Vehicle Choice (User Workflow)
3. Polaris (User Workflow)
4. Vehicle Editor (Developer Workflow)
5. Tableau (User Workflow)

There were also enhancements to existing workflows such as the addition of a dynamic tab that adds the ability to perform parametric studies and SOC correction on any of the single vehicle run workflows. Also, new UIs were created to view and modify a cycle and to perform and define an Acceleration Test (e.g., 0-60mph run)

The AMBER Smart Mobility workflow integrates the Stochastic Vehicle Trip Creator (SVTrip), which is another tool developed at Argonne, with outputs from Polaris, and vehicle models from Autonomie to produce a new integrated workflow. This workflow combines the strengths of each of these tools to perform novel analyses.

Autonomie often requires domain specific knowledge to set up and run a vehicle. For new users, unfamiliar with vehicle architectures, the standard interface with all of its options is difficult to use. The Vehicle Choice UI addresses these issues, by providing a list of vehicles currently on the road. The user can select any number of these vehicles by make and model and run simulations on any drive cycle or test procedure. The backend uses the vehicle choice database compiled at Argonne to populate Autonomie models to create representative

vehicles. These tools can be leveraged in the future in many additional workflows. For example, this workflow can be used to run vehicles of a specific make and model distribution on POLARIS cycles.

The POLARIS workflow allows one to set up scenarios in POLARIS and run them from AMBER. This shows the flexibility of the AMBER framework and the potential of the tool to link POLARIS directly with Autonomie and SVTrip. Using AMBER one would be able to design a scenario in POLARIS and seamlessly run vehicles from the vehicle choice database on POLARIS cycles to predict the fuel consumption of a city.

All of Matlab backend logic was redesigned to take full advantage of the new AMBER framework. The process file format and workflow file formats were radically redesigned to simply the addition of new procedures for a user. They help support OEMs who require the simplest and quickest ways to get their code to function within AMBER.

In addition to helping OEMs, such as Ford and GM, use their code in AMBER, the interface for defining an action within a workflow is opened up and documented. One just references the correct dll in a Visual Studio solution, and they just implement the `AMBER.Core.Interop.IProcessStepEditorInitializer` interface.

Conclusions

A new version of Autonomie was released this year, which included numerous new features developed based on feedback from DOE and the user community. A new limited beta of AMBER was also released this year. AMBER is the new future looking Autonomie, which will let Autonomie scale and adapt to the changes in the industry as new technologies are investigated and added to the DOE research portfolio. Tools such as POLARIS, SVTrip and RoadRunner can be linked together to answer the questions of tomorrow today.

Products

- Autonomie REV15 Service Pack 2
- Autonomie for MBSE Workflows 0.2

Key Publications

A Rousseau, Aymeric; Pagerit, Sylvain; Delaughter, Paul; Juskiewicz, Michael; Sharer, Phillip; Vijayagopal, Ram "**AMBER A New Architecture for Flexible MBSE Workflows**" 2017 IEEE Vehicle Power and Propulsion Conference

VI.2 Evaluate and Maximize VTO Energy Benefits Considering Trade-off between Energy and Cost (Vehicle Component Sizing Process)

Namdoo Kim, Principal Investigator

Argonne National Laboratory
9700 S. Cass Avenue, Bldg. 362
Argonne, IL 60439
Phone: (630) 252-2843
E-mail: nkim@anl.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

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Total Project Cost: \$200,000

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DOE share: \$200,000

Non-DOE share: \$0

Project Introduction

Background

In order to maximize the impact of each component technology, it is necessary to ensure that the control parameters are optimized for technology specific capabilities. While impact of engine technology changes and lightweighting were carried out under this project, this report describes the details of the optimization technique and its impact on energy consumption of the vehicle. Using this technique will ensure a fair comparison of vehicle technology capabilities.

Component sizing is one of the most important problems in the design process of a vehicle powertrain, since it directly affects the vehicle's fuel economy and dynamic performance. The problem is magnified because, as interest in electrified vehicles grows, powertrain structures that have multiple power sources become increasingly complicated. Accordingly, optimization of a vehicle's component sizes and of parameters such as engine power, electric motor power, and gear ratio, while satisfying constraints such as the acceleration performance of the vehicle, becomes a more complicated problem. Such problems need to be solved to design and evaluate powertrain configurations and to evaluate component technologies at the vehicle level.

Introduction

To evaluate a vehicle's performance relative to component size variations, a process is needed to search for the best combination of component sizes. In addition, during the sizing process, it is necessary to adjust the vehicle control strategy with respect to each component size combination. Various approaches to the vehicle configuration design and sizing problem have been reported [1–4]. However, these studies are mainly limited to a specific configuration or, in some cases, use a backward-looking vehicle simulator, so the dynamic performance of the vehicle cannot be considered explicitly. Our previous research created a rule-based sizing algorithm for various vehicle types using the forward-looking vehicle simulator, Autonomie [5]. Based on this earlier work, the component sizing process is developed using Pounders (Practical Optimization Using NO Derivatives for sums of Squares) [6], a simulation-based optimization algorithm created at Argonne National Laboratory by the Mathematics and Computer Science Division.

Objectives & Accomplishments

Objective

The objective is to develop algorithms for proper component sizing based on an optimization algorithm called “Pounder” (Practical Optimization Using NO Derivatives for sums of Squares), in order to rigorously evaluate

the impact of the Vehicle Technologies Office (VTO) technologies on fuel displacement and the costs of advanced vehicles.

Accomplishments

- Argonne continues to develop and validate rule-based sizing algorithms for various vehicle types using the forward-looking vehicle simulator, Autonomie.
- A sizing process was developed using an optimization algorithm, Pounders.
- Instead of applying a rule-based process, Pounders searches for the best component size combination.
- The optimization problem is defined as minimizing fuel consumption when the dynamic performance of the vehicle is given as a constraint.
- The process is tested by applying it to a conventional internal combustion engine-based vehicle to decide optimal engine power, and a hybrid electric vehicle to determine optimal engine and motor size.
- Built in updated Pounders optimization for the optimization process in Autonomie R15SP2.

Future Achievements

- We will Combine the algorithm for transmission gear ratio with the shift parameter to co-optimize the gear ratio selection with the shift parameter optimization.
- We will co-optimize the gear ratio selection and component sizing algorithms to simultaneously meet vehicle technical specifications and minimize energy consumption.

Approach

In this study, we present an optimization process for a conventional internal combustion engine (ICE) based vehicle and a parallel high-efficiency vehicle (HEV). For the conventional vehicle, we used a powertrain model with 6-speed automatic transmission. The assumptions used in the vehicle simulation are presented in Table VI.2-1.

Table VI.2-1 - Specifications for Vehicle Models

Parameters	Wheel Radius	Drag Coefficient	Frontal Area	Transmission	Final Drive Ratio	Vehicle Mass
Conv. Model	0.30 m	0.31	2.35 m ²	6-speed automatic	3.31	1721 kg (default)
HEV Model	0.30 m	0.30	2.35 m ²	6-speed automatic	3.65	1775 kg (default)

First, we optimized engine power size for a conventional ICE-based vehicle to minimize total fuel consumption by the vehicle on the Urban Dynamometer Driving Schedule (UDDS). To optimize the HEV powertrain, engine size and motor size are optimized together. In both cases, the optimization problems can be defined as follows:

$$\min_r \text{fuel consumption}(r)$$

$$\text{s. t. } l \leq r \leq u, c_i(r) \leq 0, i = 1,2,3, \dots, n$$

where fuel consumption (r) is the total fuel consumption in the UDDS cycle, to be minimized over the variable r , which is engine power or motor power. The variable r has lower limit l and upper limit u ; $c_i(r)$ is the driving performance constraint and n is the number of constraints.

During the sizing processes, we use Pounders to maximize the fuel economy performance of the vehicle. Optimization variables and conditions for the optimization sizing process are given in Table VI.2-2. Minimum and maximum values of the variables are determined on the basis of the values in the default model. To facilitate the comparison, the 0–60 mph acceleration time constraints for Pounders are defined to be the same as for the rule-based sizing process.

Table VI.2-2 - Conditions for Optimization Process

Optimization Parameters	Engine Peak Power		Electric Motor Peak Power		0–60 mph Acceleration Time		Time Percentage Missed for Tracing Cycle	
	min	max	min	max	min	max	min	max
Conv. Model	100 kW	200 kW	-	-	0 sec	9.01 sec	0%	0.1%
HEV Model	100 kW	150 kW	20 kW	60 kW	0 sec	8.43 sec	0%	0.1%

Results

For both the conventional vehicle and the HEV, component power is optimized and the results of the sizing process using the optimization algorithm are compared with those from the rule-based sizing process. Table VI.2-3 presents the results from Pounders and the results from the rule-based sizing process.

Table VI.2-3 - Sizing Results

		Engine Power, kW	Motor Power, kW	Vehicle Mass, kg	0–60 mph Acceleration, sec	Fuel Cons. l/100 km
Conv.	Rule-based	146.2	-	1,744	9.01	8.59
	Optimization	143.4 (-1.9%)	-	1,742 (-0.1%)	9.01 (0%)	8.54 (-0.6%)
HEV	Rule-based	129.4	37.6	1,782	8.43	5.52
	Optimization	115.3 (-11%)	46.8 (24.4%)	1,777 (-0.3%)	8.43 (0%)	5.43 (-1.6%)

The simulation produces an engine peak power of 143.4 kW as the optimal value for the optimization-based sizing process. This is similar to the result from the rule-based sizing process, 146.2 kW. Fuel consumption based on the optimization-based sizing process is 8.54 L/100 km, which is better than the 8.59 L/100 km obtained from the rule-based sizing process; the acceleration time performance is the same, which is possible because of the reduced vehicle mass, while the engine peak power decreases slightly.

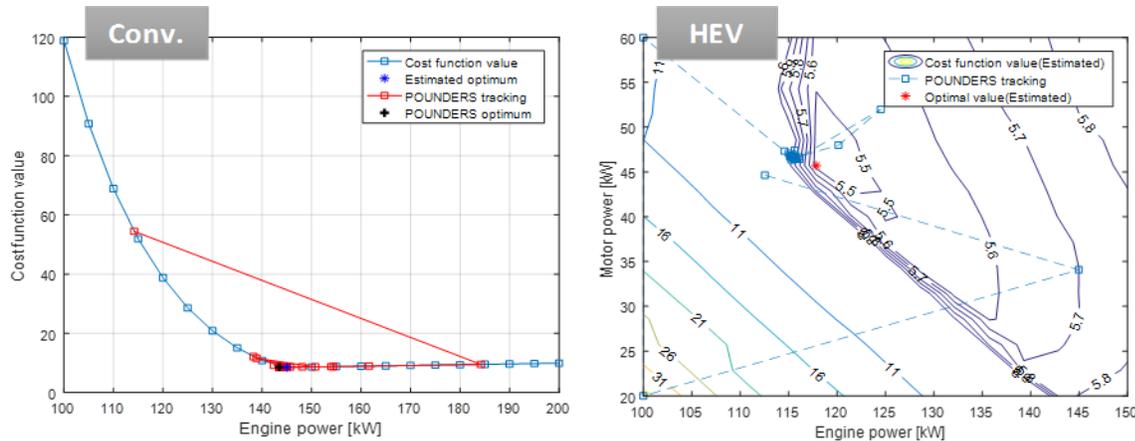


Figure VI.2-1 - Simulation Results of the Sizing Process for Conventional Vehicle (left) and HEV (right)

For the HEV, we found that the optimal engine peak power is 115.3 kW, and the motor peak power is 46.8 kW. Compared with the results from the rule-based sizing process, engine peak power is reduced by 10.9%, motor peak power is increased by 24.4%, and fuel consumption is improved by 1.6%. Figure VI.2-1 shows the contour of the estimated cost function value as a function of the engine and motor power. We investigate combinations of engine peak power and motor peak power using simulations to validate the sizing process results. The simulation results show that the point found in the sizing process approaches the lowest value of the investigated points. This indicates that we found the optimal component sizes for the engine and motor power for minimizing fuel consumption while satisfying the acceleration time constraints.

Conclusions

This study presents a sizing process using an optimization algorithm. The newly proposed sizing process is based on using an optimization algorithm produced Pounders and Autonomie. We tested the sizing process for a conventional vehicle's engine power, and for an HEV's engine and motor power. The sizing processes minimize fuel consumption while satisfying requirements for the vehicle's dynamic performance. The sizing results show that better fuel economy could be acquired from the sizing process using Pounders than from using the rule-based sizing process. The sizing process developed in this study could be used for various vehicle types and powertrains.

Key Publications

1. H. Lee, S. W. Cha, N. Kim, J. Jeong, R. Vijayagopal, and A. Rousseau, "Development of vehicle component sizing process using optimization algorithm," the FISITA World Automotive Congress 2017, December 11–14, 2017, Belfort, France.

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1. V. Madanipour, M. Montazeri-Gh, and M. Mahmoudi-k, "Optimization of the component sizing for a plug-in hybrid electric vehicle using a genetic algorithm," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, Vol. 230, Issue 5, April 2016, pp. 692–708.
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5. N. Kim, A. Moawad, V. Ram, and A. Rousseau, “Validation of sizing algorithm for several vehicle powertrains,” presented at the FISITA World Automotive Congress 2016, September 26–30, 2016, Busan, Korea.
6. S. M. Wild, “Solving derivative-free nonlinear least squares problems with POUNDERS,” Argonne National Laboratory Preprint, ANL/MCS-P5120-0414, 2014.

VI.3 TNC Vehicle Thermal Model Validation (GM Volt Gen 2 E-REV)

Namdoo Kim, Principal Investigator

Argonne National Laboratory
 9700 S. Cass Avenue, Bldg. 362
 Argonne, IL 60439
 Phone: (630) 252-2843
 E-mail: nkim@anl.gov

David Anderson, Program Manager

U.S. Department of Energy
 Phone: (202) 287-5688
 E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016

End Date: September 30, 2017

Total Project Cost: \$150,000

DOE share: \$150,000

Non-DOE share: \$0

Project Introduction

Background

Argonne has been working with the U.S. Department of Energy (DOE) and the automotive industry to provide informative analysis results of advanced vehicles to the public [1–3]. For this purpose, the Advanced Powertrain Research Facility (APRF) is equipped with two-wheel and four-wheel drive dynamometers, and vehicle performance characteristics, such as fuel economy and emissions, are evaluated on bench dynamometers. For many years, Argonne has tested, analyzed, and validated the models for conventional, hybrid electric, plug-in hybrid electric, and battery electric vehicles (EVs), including their thermal aspects; Argonne is continuing its efforts to provide more analysis results for advanced vehicles.

Introduction

The General Motors (GM) Volt vehicle is the first electric range-extended vehicle to be manufactured on a large scale; it went on sale in December in 2010. Its successful introduction in the worldwide vehicle market, especially in the U.S. market, has resulted in the world's all-time best-selling plug-in hybrid vehicle as of December 2016. The latest version of the vehicle, the second generation, was introduced at the January 2015 North American International Auto Show and was available in the market on October 2015, as a 2016 model year [4]. In fiscal year 2017, we analyzed vehicle operation based on the Volt second-generation test data and developed the vehicle model representative in Autonomie, including sensitivity to temperature.

Objectives & Accomplishments

Objectives

- The objective of this study is to develop and validate the vehicle model of the 2016 Chevrolet Volt (second-generation VOLTEC) with sensitivity to thermal conditions using dynamometer test data obtained from Argonne's Advanced Powertrain Research Facility (APRF).

Accomplishments

- Analyzed vehicle operation based on the Chevrolet Volt second-generation dynamometer test data and compared system efficiency with the previous system.
- Developed and validated supervisory control logic and the vehicle model in Autonomie, including sensitivity to temperature.

Future Achievements

- The impacts from thermal conditions will be combined with the impacts from additional real-world scenarios (fleet distribution, grade, ITS) to provide a realistic evaluation of technology benefits.

Approach

This study presents an analysis of the second generation of the Volt powertrain system, called the new Voltec system, by comparing its system efficiency with the previous system. The model year (MY) 2016 Volt supervisory control strategy and the component performance models have been developed through test data analysis. Finally, the completed vehicle model was validated with test data.

Table VI.3-1 presents the main changes in the powertrain component of the MY 2016 Volt. The most significant change compared to the previous version is that the vehicle has a new transaxle configuration and operation modes.

Table VI.3-1 - Differences between MY 2011 Volt and MY 2016 Volt

Parameter	MY 2011	MY 2016																																												
Configuration																																														
Operation Mode	<table border="1"> <thead> <tr> <th>Mode</th> <th>BK1</th> <th>CL1</th> <th>CL2</th> </tr> </thead> <tbody> <tr> <td>EV1</td> <td>closed</td> <td>open</td> <td>open</td> </tr> <tr> <td>EV2</td> <td>open</td> <td>open</td> <td>closed</td> </tr> <tr> <td>Series</td> <td>closed</td> <td>closed</td> <td>open</td> </tr> <tr> <td>Output power split</td> <td>open</td> <td>closed</td> <td>closed</td> </tr> </tbody> </table>	Mode	BK1	CL1	CL2	EV1	closed	open	open	EV2	open	open	closed	Series	closed	closed	open	Output power split	open	closed	closed	<table border="1"> <thead> <tr> <th>Mode</th> <th>BK1</th> <th>CL1</th> <th>OWC</th> </tr> </thead> <tbody> <tr> <td>EV1</td> <td>closed</td> <td>open</td> <td>open</td> </tr> <tr> <td>EV2</td> <td>closed</td> <td>open</td> <td>closed</td> </tr> <tr> <td>Low extended range</td> <td>closed</td> <td>open</td> <td>open</td> </tr> <tr> <td>Fixed ratio</td> <td>closed</td> <td>closed</td> <td>open</td> </tr> <tr> <td>High extended range</td> <td>open</td> <td>closed</td> <td>open</td> </tr> </tbody> </table>	Mode	BK1	CL1	OWC	EV1	closed	open	open	EV2	closed	open	closed	Low extended range	closed	open	open	Fixed ratio	closed	closed	open	High extended range	open	closed	open
Mode	BK1	CL1	CL2																																											
EV1	closed	open	open																																											
EV2	open	open	closed																																											
Series	closed	closed	open																																											
Output power split	open	closed	closed																																											
Mode	BK1	CL1	OWC																																											
EV1	closed	open	open																																											
EV2	closed	open	closed																																											
Low extended range	closed	open	open																																											
Fixed ratio	closed	closed	open																																											
High extended range	open	closed	open																																											

The efficiency of the electrically variable transmission was analyzed as a function of input speed, input torque, and speed ratio. The power-split configurations have both all-mechanical and electro-mechanical paths that combine the planetary gear set and two electric machines. Figure VI.3-1 plots the electro-mechanical power ratio and the transmission efficiency with respect to the speed ratio (SR) for both transaxle configurations.

For the first-generation Voltec, the transmission efficiency of the high SR range is relatively low because the electrical machines have relatively low efficiency. For the second-generation Voltec, the electro-mechanical power ratio becomes zero at both mechanical points (MP1, MP2). It maintains the input-split mode until the speed ratio reaches MP1. The fixed gear ratio (FG) comes from locking up the input-split mode, so the speed, torque, and power from the engine go through the torque multiplication of the planetary gear sets. The two-mode power-split system with one fixed gear ratio point can lower the requirement for electric machine

power, thus allowing a further decrease in component size while still providing the power to achieve vehicle performance targets.

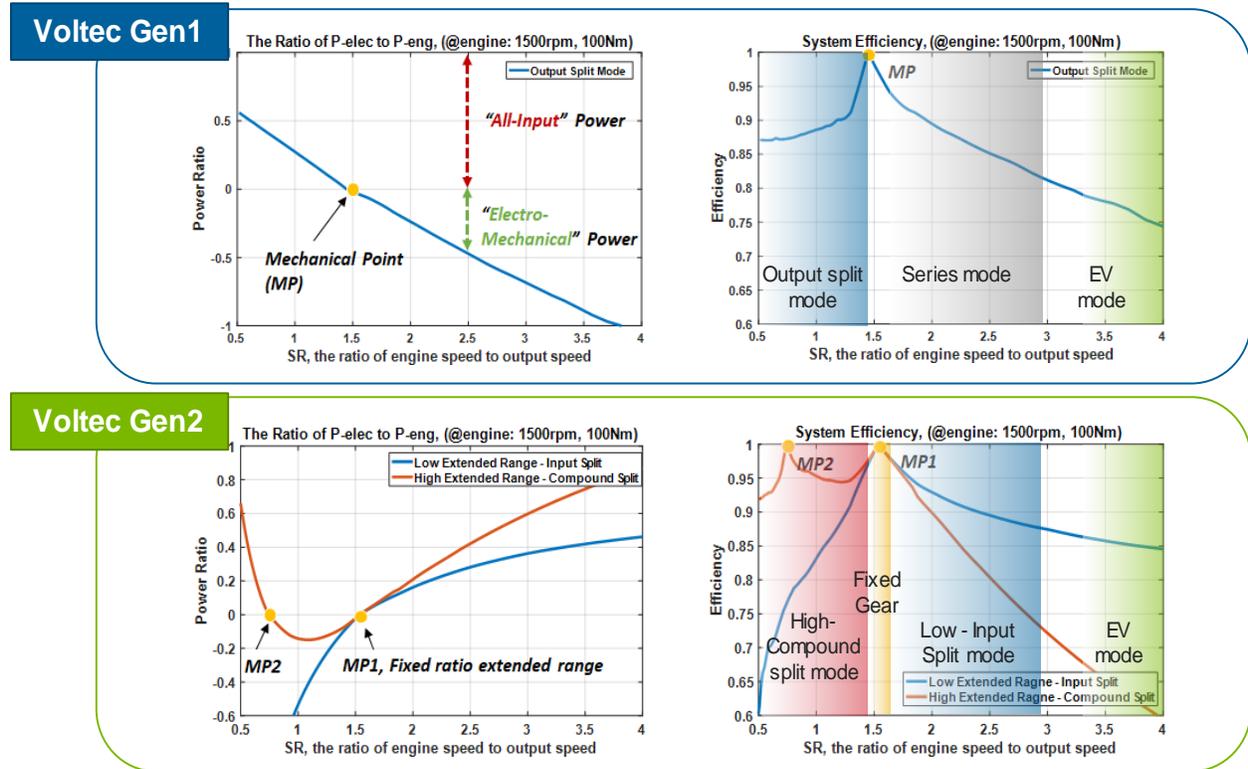


Figure VI.3-1 - Powertrain Characteristics

Results

Control Analysis

To understand supervisory control, we introduced four main mode: engine on/off control, transmission mode control strategy, state of charge (SOC) balancing control, and detailed component control concepts. The engine on/off determines the operation mode, and the SOC balancing determines the power management between the engine power and the battery power.

The Volt is an EV with extended range, which can operate with full vehicle performance on battery power alone, without using its engine, so long as the battery pack has available energy. After the battery SOC decreases to a certain point, the engine turns on more often and the battery SOC is maintained within a narrow range; this is the charge sustaining (CS) mode. Figure VI.3-2 shows the points when the vehicle driving mode changes from CD to CS mode under normal ambient temperature using the test data for the first- and second-generation Voltec. The results show that the engine turns on early if the SOC is too low, in order to preserve the battery SOC.

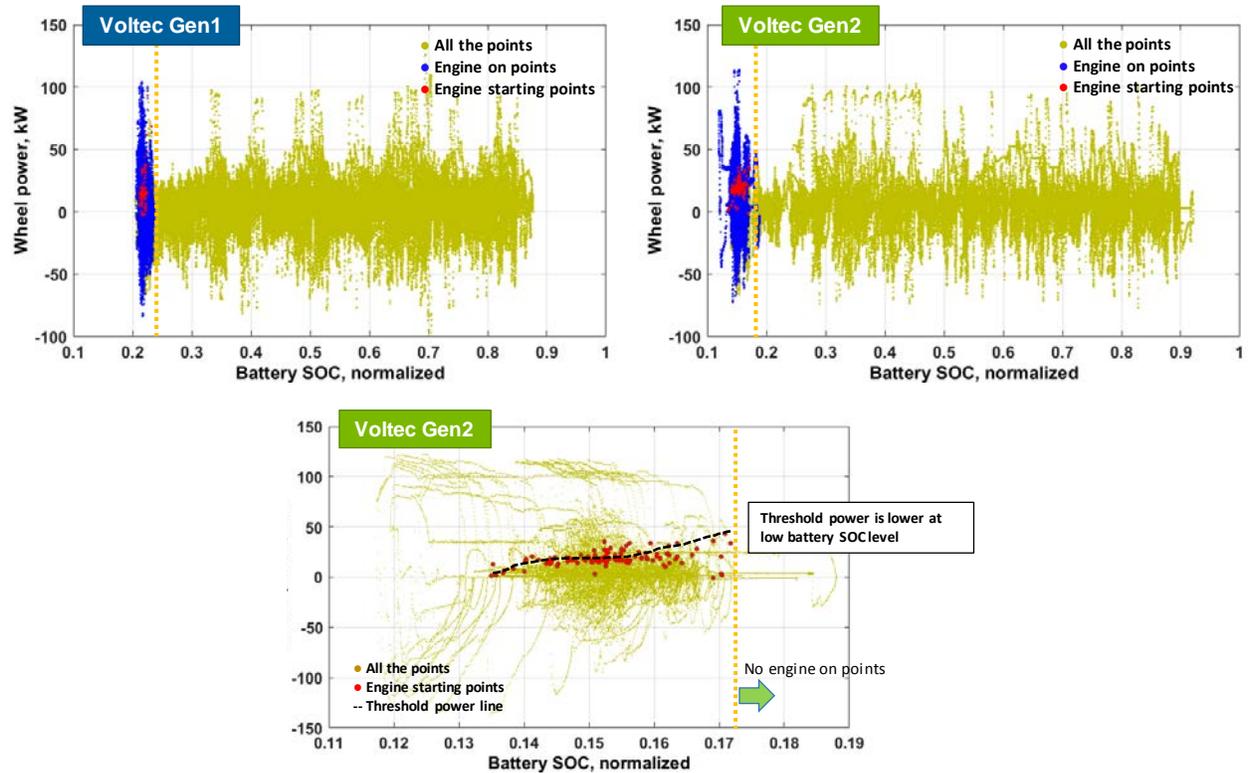


Figure VI.3-2 - Wheel Power According to Battery SOC When the Engine Turns On

The second-generation Voltec has five driving modes, including two EV operations and three extended-range operations. In EV operations, the transitions from EV1 mode to EV2 mode are easier compared to the previous system, because clutch engagement or disengagement is not required. Figure VI.3-3 shows that the EV2 mode is used to start the vehicle and the EV2 mode is selected when electric machine 1 reaches its maximum torque in EV1 mode, to cover the short demand of wheel torque by using both electric machines. Figure VI.3-3 shows that the fixed gear ratio mode supplements the low extended mode when the vehicle speed is over 30 mph.

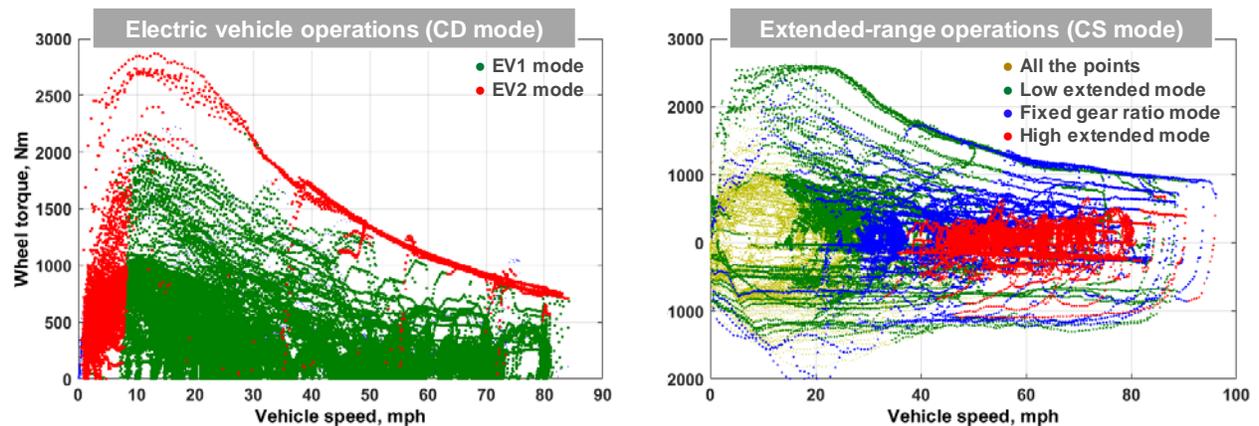


Figure VI.3-3 - Wheel Torque According to Vehicle Speed for Each Driving Mode

Once the operation mode is chosen, the battery power demand is determined by the proportional control power, which also determines the engine power demand by subtracting the battery power demand from the driver power demand. The control strategy and the performance are also analyzed under various thermal

conditions such as cold or hot ambient temperature and soaked or warmed-up vehicle. Figure VI.3-4 shows no engine is on in CD mode if the heater is off (i.e., normal or hot ambient temperature conditions). However, if heating is needed in cold ambient temperatures, the engine temperature is kept over 50°C.

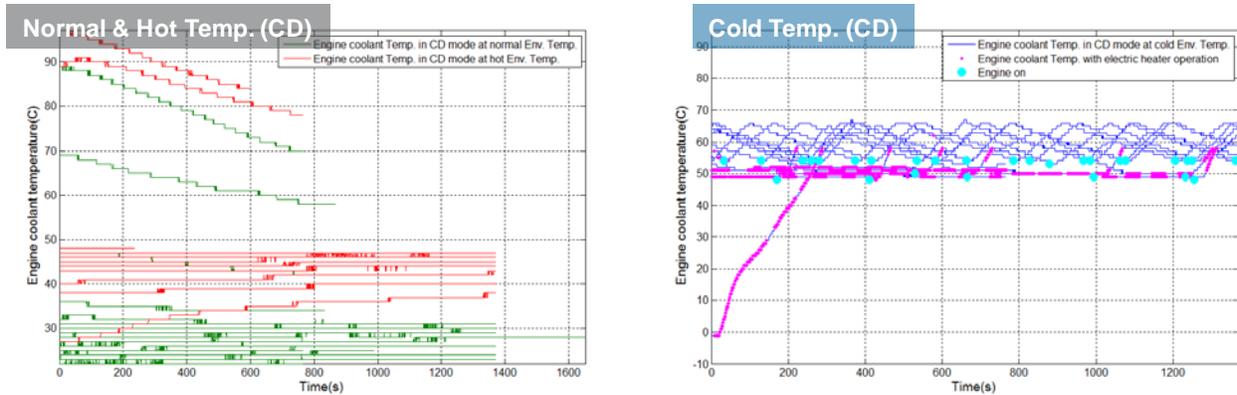


Figure VI.3-4 - Engine Coolant Temperature during CD Mode

Validation

We implemented a model of the vehicle, including calibrated plants and controllers, in Autonomie. The validation process is iterative, and combines data analysis, model development, and model calibration shows how the main signals in the test and in the simulation compare with each other and demonstrates the successful validation of the vehicle.

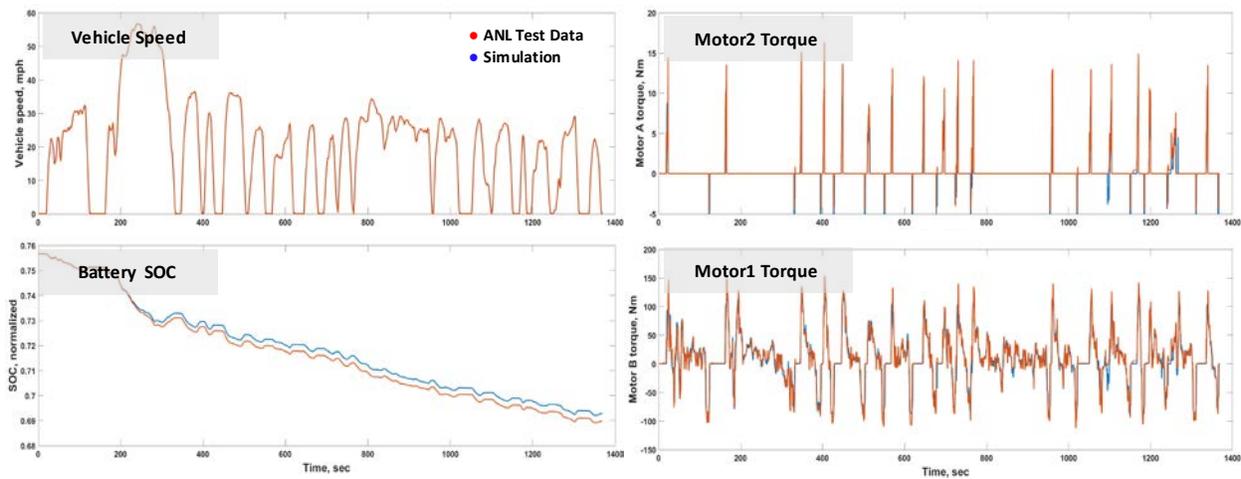


Figure VI.3-5 - Comparison of Test and Simulation Signals (UDDS cycle, normal ambient temperature)

Conclusions

- The improvements of the Volt second-generation powertrain system have been assessed by comparing system efficiency with the previous generation.
- The vehicle energy management strategy analysis has been completed using APRF dynamometer test data.
- The full vehicle model has been developed and validated in Autonomie.

Key Publications

1. N. Kim, S. Choi, J. Jeong, R. Vijayagopal, K. Stutenberg, and A. Rousseau, "Vehicle level control analysis for Voltec Powertrain," Proceedings of the 30th Electric Vehicle Symposium (EVS30) Conference, Stuttgart, Germany, October 2017.
4. J. Jeong, S. Choi, N. Kim, K. Stutenberg, and A. Rousseau, "Model validation of the Chevrolet Volt 2016," submitted for SAE World Congress 2018.

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2. J. Jeong, W. Lee, N. Kim, K. Stutenberg, et al., "Control Analysis and Model Validation for BMW i3 Range Extender," *SAE Technical Paper 2017-01-1152*, 2017, doi:10.4271/2017-01-1152.
3. H. Lohse-Busch, M. Duoba, E. Rask, K. Stutenberg, V. Gowri, L. Slezak, and D. Anderson, "Ambient Temperature (20°F, 72°F and 95°F) Impact on Fuel and Energy Consumption for Several Conventional Vehicles, Hybrid and Plug-In Hybrid Electric Vehicles and Battery Electric Vehicle," *SAE Tech. Pap.* 2013-01-1462, October 2016, doi:10.4271/2013-01-1462.
4. B. Conlon, T. Blohm, M. Harpster, A. Holmes, et al., "The Next Generation "Voltec" Extended Range EV Propulsion System," *SAE Int. J. Alt. Power.* 4(2):248–259, 2015, doi:10.4271/2015-01-1152.

VI.4 Vehicle System Research

Kevin Stutenberg, Principal Investigator

Argonne National Laboratory
 9700 South Cass Ave
 Argonne, IL 60439
 Phone: (630) 252-6788
 E-mail: kstutenberg@anl.gov

David Anderson, Program Manager

U.S. Department of Energy
 Phone: (202) 287-5688
 E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2016	End Date: September 30, 2017	
Total Project Cost: \$1,300,000	DOE share: \$1,300,000	Non-DOE share: \$0

Project Introduction

Since its inception, the Advanced Powertrain Research Facility (APRF) has been testing advanced-technology vehicles to benchmark the latest automotive technologies and components for the U.S. Department of Energy (DOE). A dozen vehicles with interesting powertrains technologies were tested in the laboratory, and a number of these vehicles were test under special partnership projects.

Objectives

Argonne is providing public and independent data to enable vehicle system research and modeling and simulation work. Two select highlights of FY 2017 are a study on the evolution of the latest plug-in hybrid powertrain from Toyota and a study of the impact of active transmission warm up on off-cycle CAFE credits.

Approach

In order to evaluate the instrumented test vehicles in a variety of real-world conditions, the 4WD chassis dynamometer of the APRF is EPA 5-cycle capable. The test cell includes a thermal chamber and an air-handling unit with a large refrigeration system that enables vehicle testing at the EPA "Cold CO Test" ambient temperature of 20°F (-7°C), the standard test temperatures of 72°F (25°C), as well as the "SC03" test temperature of 95°F (35°C). Additionally, ambient test temperatures of 0°F (-17°C), and 40°F (4.5°C) may be used. All temperatures can be evaluated with or without solar emulation lamps providing up to 850 W/m² of radiant sun energy. The test cell is shown in Figure VI.4-1.

The APRF benchmark program goes well beyond the standard tests performed for EPA certification of fuel economy and emissions. To fully characterize the powertrain and the individual components the instrumented powertrains are tested on a wide range of ambient temperatures, drive cycles, performance tests and vehicle/component mapping tests.

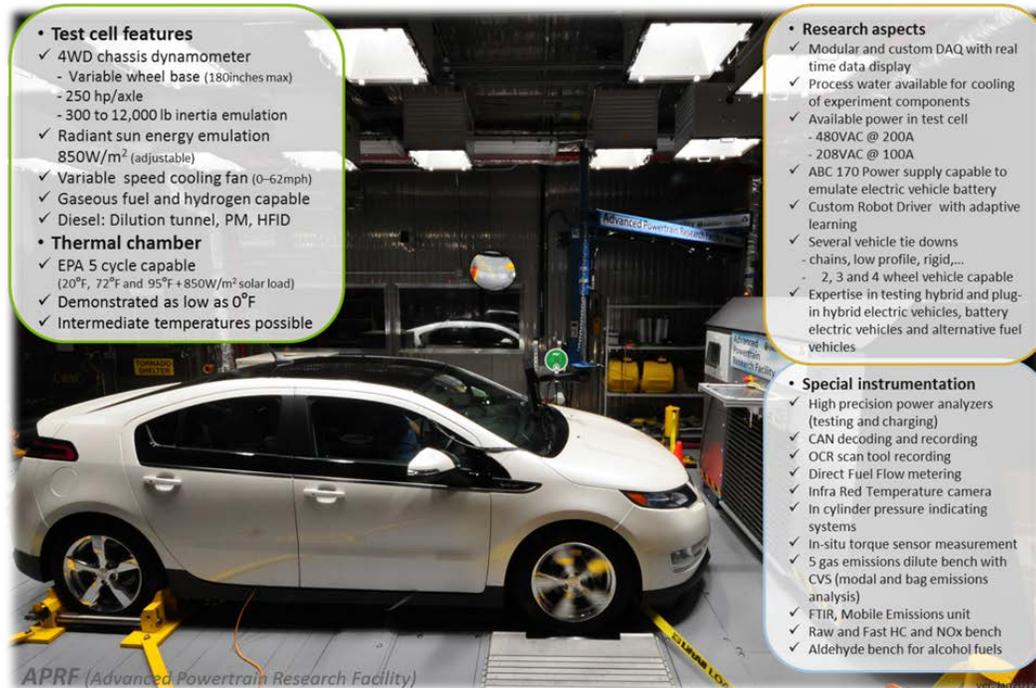


Figure VI.4-1 - Illustration of the chassis dynamometer in thermal chamber long with facility capabilities

D3 is a public web portal of highly detailed accurate public and independent vehicle test data, of critical utility in the research community. This web-based portal to Argonne vehicle test data is designed to provide access to dynamometer data that are typically too expensive for most research institutions to generate. Shared data is intended to enhance the understanding of system-level interactions of advanced vehicle technologies for researchers, students, and professionals engaged in energy-efficient vehicle research, development, or education. Figure VI.4-2 shows the structure and content of the database.

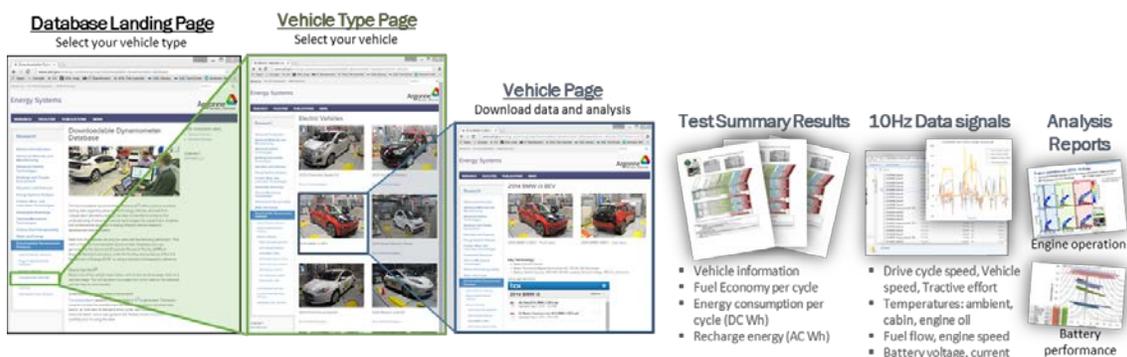


Figure VI.4-2 - Map of Downloadable Dynamometer Database content

Results

2017 Toyota Prius Prime comparison to 2013 Toyota Prius PHEV

This investigation is a comparison of the first and second generation plug-in hybrid Prius based on the data from the technology assessment and laboratory testing performed at Argonne. The second generation plug-in

Prius is capable of full performance in electric mode. The first generation was only able to complete a UDDS and highway cycle and electric mode, but at higher acceleration rates and power demands the internal combustion engine was needed to provide the requested performance. The new powertrain uses a larger MG2 motor of 53 kW, a one way clutch on the engine to enable both electric motors to drive the wheels without over speeding the engine, and a new battery pack with higher power capability (350V) and larger capacity (8.8 kWh). The 2017 Prius Prime is capable of completing almost three US06 drive cycles without using the internal combustion engine, in contrast the 2013 Toyota PHEV needed the internal combustion engine during charge depleting operation due to the high power demands as seen in Figure VI.4-3. The smaller electric performance envelope of the first generation Prius results in a much slower charge depletion rate.

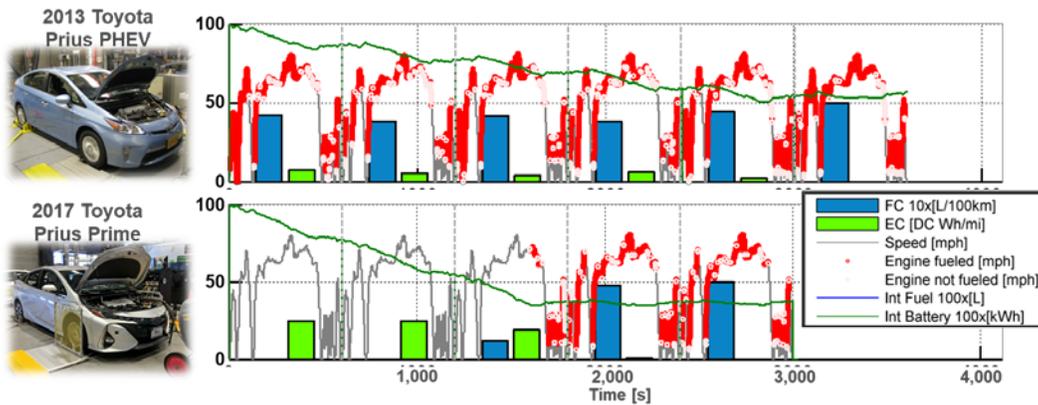


Figure VI.4-3 - Charge depleting powertrain performance on the US06 drive cycle for the 2013 and 2017 plug-in Prius

The battery pack in the second-generation powertrain has a nominal voltage of 350 V as compared to 215 V for the first generation as seen in Figure VI.4-4. Both battery packs can deliver around 200 A of current, but the higher voltage enables the second-generation powertrain to deliver up to 75 kW which is double the power delivery of the battery pack from the first generation powertrain.

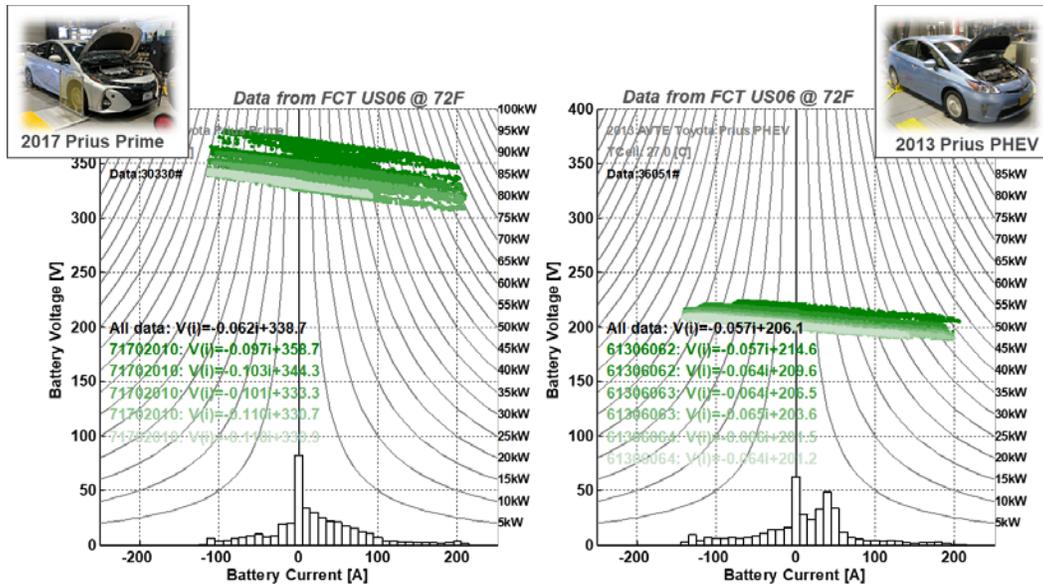


Figure VI.4-4 - Battery pack performance on the US06 drive cycle for the 2013 and 2017 plug-in Prius

The increased electric power envelope allows the 2017 Prius to not use the engine in charge depleting mode and in charge sustaining mode it operates the engine at higher and more efficient loads as seen in Figure VI.4-5. The 2013 Prius needs the engine in charge depleting mode to supplement the smaller electric power envelope, and this results in the engine operating at lower and less efficient loads in order to discharge the battery energy.

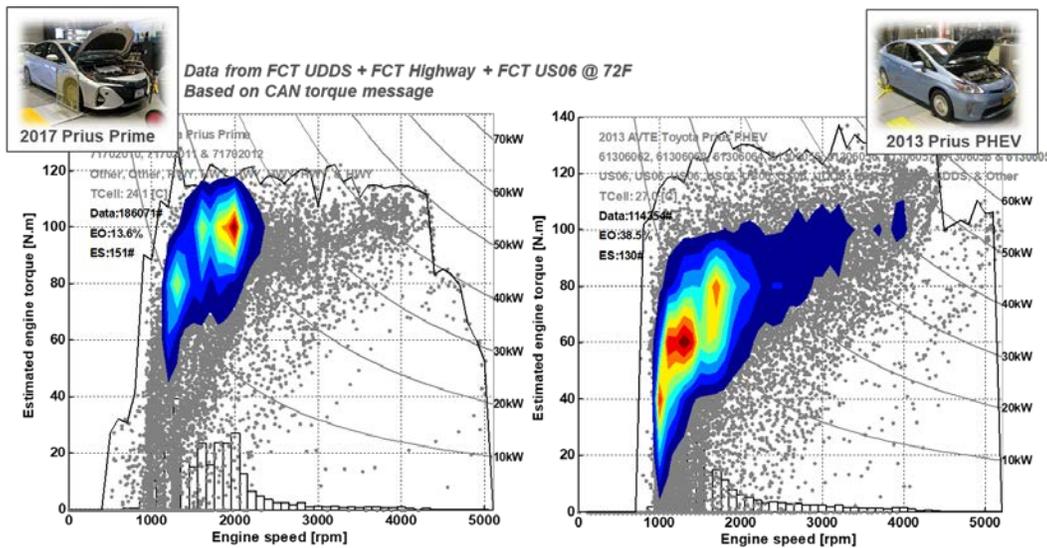


Figure VI.4-5 - Engine performance on US06 cycle for the 2013 and 2017 plug-in Prius

Toyota maintained a power splits hybrid architecture for its second generation plug-in Prius, but through targeted component improvements enabled the vehicle to have a full performance in electric mode which enables a pure electric operation in charge depleting mode, similar to an extended range vehicle.

Argonne presented a larger plug-in hybrid study comparing seven plug-in hybrid vehicles ranging from blended plug-in hybrids to extended range hybrids and battery electric vehicles with range extender. The major finding is that the electric vehicle performance envelope in charge depleting mode will dictate the petroleum displacement rates in charge depletion mode regardless of powertrain architecture. The amount of petroleum displacement is directly proportional to the usable battery capacity. The 2013 Prius PHEV, which is a blended plug-in hybrid, and the 2017 Prius Prime, which has full performance in electric only mode, illustrate the findings of the larger study quite well.

Active transmission warm up investigation

This investigation aimed to quantify the fuel consumption and CO₂ benefit of an active transmission warm up system. To that end, a 2013 Ford Taurus equipped with a 2.0L EcoBoost engine and a factory installed active transmission warm-up (ATW) system was tested on the chassis dyno. The vehicle was modified to allow the ATW system to operate automatically as designed, and to switch the warm up system off as shown in Figure VI.4-6.

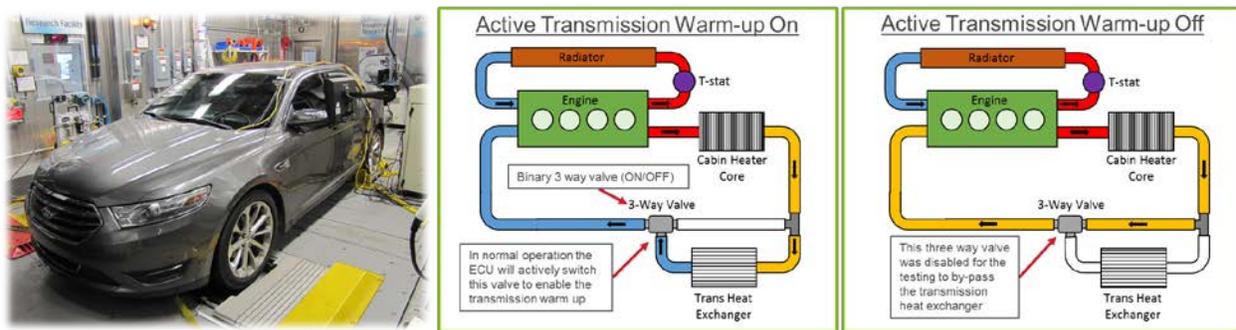


Figure VI.4-6 - The active transmission warm up system modes of the 2013 Ford Taurus test vehicle

In order to measure the fuel usage changes with and without the active transmission warm up system several test technics were applied: a statistical number of repeats, thermally consistent test days (consistent day to day timing), keeping the vehicle on the dyno for the duration of the testing, using a repeatable robot driver, and a number of other factors.

Figure VI.4-7 shows the difference in transmission fluid temperature as well as the fuel consumption results with the active transmission warm-up system controlled by the vehicle (ATW Auto) and the system manually turned off (ATW Off) on a cold start UDDS at 72°F. Fuel savings of the active transmission warm-up system is 1.45% on the cold start UDDS at 72°F.

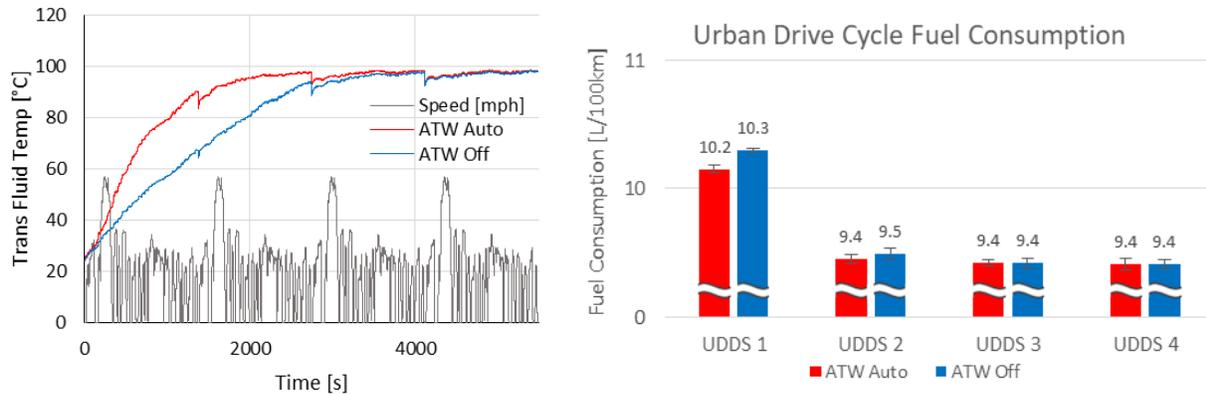


Figure VI.4-7 - Transmission fluid temperature vs. time with active transmission warm-up in Auto and Off on a UDSSx4 test at 22C ambient temperature.

The active transmission warm-up system in the test vehicle was found to produce a fuel consumption benefit of 1.45% on a cold start UDSS drive cycle at ambient temperature of 72°F and 1.28% on a cold start UDSS at 20F.

The test plan included all of the five cycle tests required in order to establish the benefit of the ATW system across the 5 cycle fuel economy label testing. Table VI.4-1 presents the statistical mean fuel consumption and CO₂ results with the ATW system On and Off. The system provides insignificant fuel savings for the label highway results which is composed of only hot start tests. The ATW system did provide a 0.85% fuel savings on the label city results.

Table VI.4-1 - Fuel consumption and CO₂ test results

5 Cycle Fuel Consumption [L/100km]				5 Cycle CO ₂ Emissions [g/mi]			
	ATW On	ATW Off	Benefit [%]		ATW On	ATW Off	Benefit [gCO ₂ /mi]
FC City	12.64	12.75	0.85	CO ₂ City	473.3	478.3	4.10
FC Hwy	9.67	9.68	0.08	CO ₂ Hwy	364.2	364.4	0.29
FC Comb	11.31	11.37	0.56	CO ₂ Comb	428.8	427.1	2.39

Based on this data, the combined 5-cycle emissions benefit of 2.39 g CO₂ /mi is actually well above the EPA off-cycle credit for cars of 1.5 g CO₂/mi. However, it is important to note that this data is representative for one specific vehicle only, the 2013 Ford Taurus 2.0L EcoBoost. An ATW system in any other vehicle may have different results.

The limits of the ATW system benefits were explored by testing the system on a long duration, constant speed drive cycle as well as a hot start HWY cycle at 20F ambient temperature. The results of these tests showed that although the maximum operating temperature of the transmission changes due to the ATW system, no significant fuel consumption benefits exist after the powertrain reaches thermal equilibrium, even in cold ambient conditions.

Furthermore, an effort to determine the maximum possible benefit of the ATW system was made by modifying the test vehicle to be able to pre-heat the transmission fluid using external heating pads. A cold start UDDSx4 test at 20F ambient temperature was then run with transmission pre-heating and compared to the same tests with ATW Auto and ATW Off. The results of this test found a 3.84% reduction in fuel consumption for the first UDDS drive cycle as compared to ATW Off and negligible benefits for cycles 2 through 4. This showed that there are major benefits still to be had with a better ATW system, but only if it can be done without negatively impacting other parts of the powertrain.

Finally, to understand the importance of thermal energy availability in other parts of the vehicle, a pair of UDDSx4 tests were run at 20F ambient temperature with the passenger compartment heat turned off. The results of these tests helped show that thermal energy is indeed very important for powertrain efficiency, with a 3.8% improvement in cold start fuel consumption when cabin heat was turned off versus on and ATW was in Auto. In addition to this, a 3.7% improvement was found when cabin heat was turned off vs on and ATW was Off. Lastly, in addition to the importance of thermal energy for powertrain efficiency, these results also showed that the benefits of active transmission warm-up were independent of the benefits from keeping cabin heat off and were in fact additive, at least in the case of the 2013 Ford Taurus.

Conclusions

Argonne has provided public an independent data, which is available for download at www.anl.gov/d3, on advanced technology vehicles. The first highlighted study shows the evolution of Toyota's plug-in hybrids powertrain and how an increased electric performance envelope increases the petroleum displacements capability of the vehicle. The second highlighted study shows that an active transmission warm-up system can save over 1% in fuel consumption on a UDDS cold start tests or 0.85% fuel consumption over the EPA five cycle fuel economy label for a 2013 Ford Taurus.

Key Publications

1. Jehlik F., "Investigation of Transmission Warming Technologies at Various Ambient Conditions ", 2017-01-0157, 2017 SAE World Congress, April 5th, 2017
2. Duoba M., Iliev S., "Evaluating Electric Driving Potential Estimates ("eVMT") Using Standard Test Methods and Utility Factors for PHEVs and BEVs.", 2017 SAE World Congress, April 5th, 2017
3. Stutenberg K., Lohse-Busch H., "Advanced Technology Vehicle Laboratory Benchmarking (Level 1 & Level 2)", 2017 U.S. DOE Vehicle Technologies Program Annual Merit Review and Peer Evaluation Meeting, June 6th, 2017
4. Stutenberg K., "EU-US evaluation of range extended electric vehicle performance at varying ambient temperatures", DOI: 10.1109/ITEC.2017.7993327, 2017 IEEE Transportation Electrification Conference and Expo (ITEC), 22-24 June 2017
5. Iliev S., "Energy Efficiency Benefits of Active Transmission Warm-up Under Real-World Operating Conditions", 2018 SAE World Congress,

VI.5 Medium- and Heavy-Duty Vehicle Field Evaluations

Kenneth Kelly, Principal Investigator

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80439
Phone: (303) 275-4465
E-mail: kenneth.kelly@nrel.gov

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 287-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: June 1, 2016

End Date: September 30, 2018

Total Project Cost: \$1,950,000

DOE share: \$1,950,000

Non-DOE share: \$0

Project Introduction

The U.S. Department of Energy's (DOE's) Vehicle Technologies Office funds a wide array of research and development projects on advanced, energy efficient vehicle technologies. Vehicle technology evaluations provide data and analysis of real-world service requirements and performance of commercial vehicles and systems to help accelerate the transition of energy-saving technologies into widespread marketplace adoption. To accomplish this, NREL has conducted analysis and reporting of advanced vehicle technologies and provided unbiased data and vehicle technology evaluations. The information generated by this project is vital to original commercial vehicle equipment manufacturers and system integrators to optimize advanced vehicle systems for energy savings, performance, and cost while meeting vocational requirements. The project also provides independent information to fleet managers to aid them in making purchase decisions that will be appropriate for the unique operational characteristics of a given vocation. Data and results contribute to the Fleet DNA database where researchers, including DOE-funded programs, can gain access to help understand real-world technology requirements and component performance and feed vehicle systems modeling efforts.

Objectives

The main goal of this project is to evaluate advanced propulsion technologies in medium- and heavy-duty vehicle applications and to provide data, detailed engineering analysis and results from an unbiased source that help inform research and development activities and facilitate the transition from research and development/prototype stage into the market viable solutions. This will be accomplished by means of the following:

- Evaluating, analyzing, and publishing results on advanced commercial vehicle technologies as compared to conventional technologies across a variety of vehicle vocations in real-world service;
- Providing detailed vehicle and powertrain component data and analysis to the research and development partners, including other vehicle programs within the U.S. Department of Energy, to support advanced vehicle technology research and development

Approach

Under this project, NREL works with fleet and/or original equipment manufacturer partners to select, test, and validate advanced technologies in commercial vehicle applications. Specific technologies are selected based on (1) their potential for reducing fuel consumption, (2) their potential for widespread commercialization, and (3) synergy with DOE research programs, including the 21st Century Truck Partnership and other DOE technology areas including electrification, energy efficient mobility, and technology integration. After a candidate vehicle technology has been identified, the National Renewable Energy Laboratory (NREL) collects vehicle data on system performance, maintenance (if available), and/or operational costs relating to the new

technology. The data is analyzed, and the results are published and presented to DOE, project teams, and at industry technical conferences. The potential for improvement in real-world service, including operational costs, maintenance, and emissions, will be compared to data collected from conventional technology vehicles.

The approach for the fiscal year 2017 (FY 2017) medium- and heavy-duty field evaluation projects included:

- Working cooperatively with commercial fleets to collect operational, performance, and cost data for advanced technologies;
- Use in-service data and advanced analytical techniques to conduct detailed duty-cycle analysis and generate representative vehicle drive/duty cycles;
- Chassis dynamometer testing of advanced and baseline control vehicles at NREL's Renewable Fuels and Lubricants (ReFUEL) laboratory;
- Use in-service vehicle and chassis dynamometer data to develop validated vehicle systems models
- High performance computing to investigate optimized power train configurations for a variety of medium- and heavy-duty vocations;
- Incorporate data into NREL's Fleet DNA database for use in other DOE research activities and with a variety of other government, industry and research partners;
- Publish and present results on new advanced technologies to DOE and other stakeholders.

The following section provides a summary of accomplishments and results from FY2017 activities. Additional details and results from previous years can be found at the NREL Commercial Vehicle Technologies website at <https://www.nrel.gov/transportation/fleettest.html>.

Results

Odyne Hybrid Systems Plug-in Hybrid Utility Truck Field Evaluation with Duke Energy

Odyne Systems of Waukesha, Wisconsin, produces a power take-off-based plug-in hybrid vehicle for medium- and heavy duty vocational vehicles in the utility and maintenance sectors (see Figure VI.5-1). The Odyne system, which interfaces with Allison transmissions, provides both tractive power for driving as well as power for auxiliary loads such work tools and heating, ventilation, and air conditioning (HVAC). Additional details on the powertrain component and architecture can be found in previous year DOE annual reports.

NREL conducted a project kick-off meeting in April 2016 with Odyne Hybrid Systems and Duke Energy's Fleet Director. Vehicles and locations for in-field data collection were identified and field data was collected from Odyne hybrid utility bucket trucks and hybrid utility vans along with conventional baseline diesel vehicles with similar duty cycles. In FY2017, NREL conducted detailed hierarchical clustering analysis of the in-service vehicle data to characterize distinct operational modes (see Figure VI.5-2 - Characteristic acceleration and aerodynamic speed plotted for Odyne vehicle trips. Color denotes the cluster that each trip belongs to) and create representative drive cycles for dynamometer testing of an Odyne large aerial truck. NREL also developed a methodology to characterize stationary, job-site operations to evaluate job-site energy use. These cycles were successfully executed on the ReFUEL dynamometer. Data collected in the field and on the dynamometer will be used to validate vehicle systems models to improve hybrid control of the Odyne vehicle.



Figure VI.5-1 - Odyne Hybrid Systems aerial bucket truck, Courtesy Odyne Systems (NREL 34043)

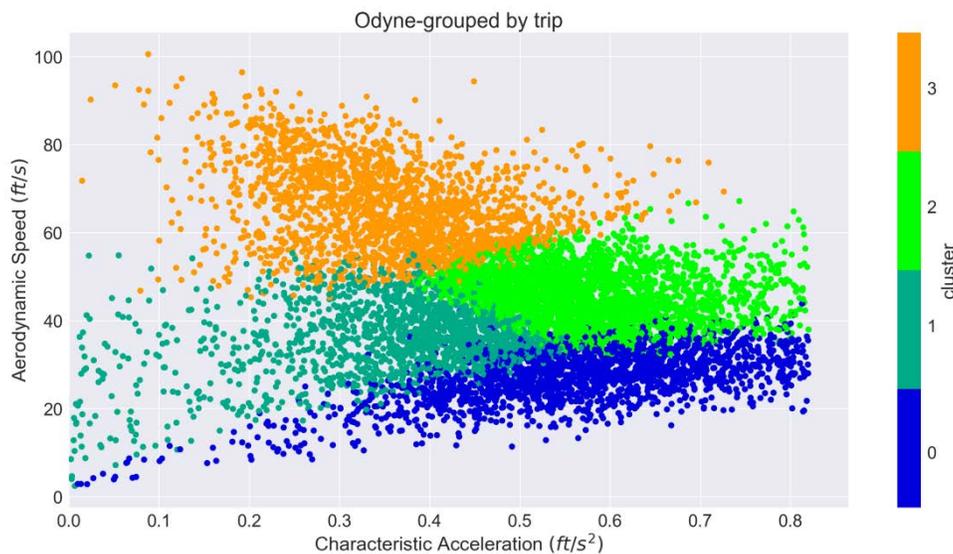


Figure VI.5-2 - Characteristic acceleration and aerodynamic speed plotted for Odyne vehicle trips. Color denotes the cluster that each trip belongs to

Electric School Bus with Bi-Directional Inverter

In FY2017, the NREL Commercial Vehicle Technologies team collected baseline school bus data from 40 vehicles operated in two California school districts and provided the data to the Fleet DNA project. A statistically representative “school bus” drive cycle was developed using NREL’s Drive-Cycle Rapid Investigation, Visualization, and Evaluation (DRIVE) drive cycle evaluation tool. The Commercial Vehicle Technologies team coordinated with NREL’s Grid Integration team to conduct testing of the electric-vehicle-to-grid (EV2G) school bus at the Energy Systems and Integration Facility (ESIF) and the ReFUEL laboratory. Chassis dynamometer testing of the TransPower EV2G school bus was completed at NREL’s ReFUEL laboratory, and IEEE 1547 and SAE J3068 interconnection testing was completed at the ESIF. Measured EV efficiency for the 4 test cycles ranged between 1.45 kWh/mile and 1.78 kWh/mile (see Figure VI.5-3) compared to preliminary on-road efficiency data that averaged 1.34 kWh/mile. AC to DC charging efficiency was determined to be 95.6% while AC charge to DC discharge efficiency was determined to be 87.8%.

The chassis dynamometer test data was used to develop and validate an EV school bus model using NREL’s FASTSim vehicle model. Vehicle simulations were conducted using NREL’s high performance computing to simulate real-world driving from over 400 vehicles days of school bus driving are available in the FleetDNA database. The simulated EV energy efficiency showed a modal value of 1.25 kWh/mile ranging from 0.6 to 2.3 kWh/mile (see Figure VI.5-3). The simulated results show the dependency of efficiency on average speed and kinetic intensity and give an initial estimate of electric driving range for the distribution of real-world school

bus routes (see Figure VI.5-4). Over the next fiscal year, NREL will collaborate with TransPower to collect and analyze on-road data from six EV2G school buses from three school districts as they are deployed in the 2017/18 school year. The findings will be compiled and a final technical report of project status and outcomes will be published.

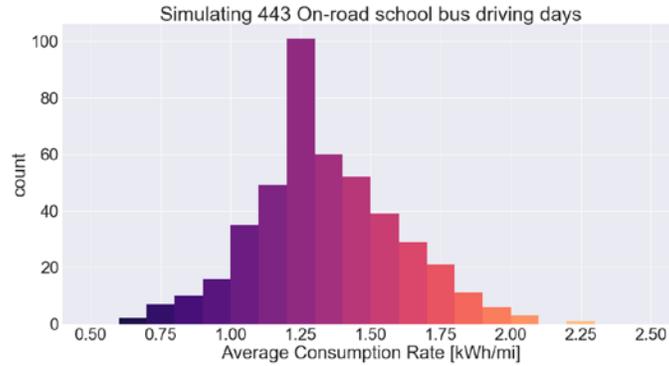


Figure VI.5-3 - Distribution of modeled EV school bus energy consumption per mile

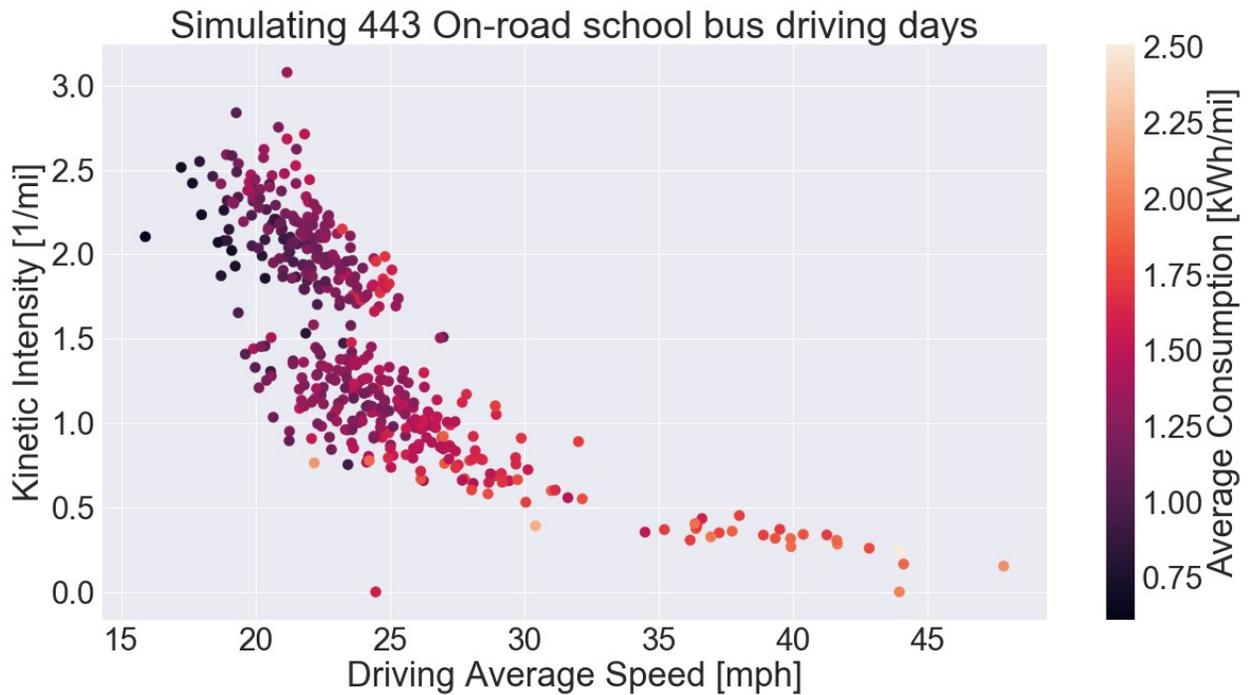


Figure VI.5-4 - EV school bus energy consumption simulated on over 400 real-world school bus drive cycles

Parker Hannifin Hydraulic Hybrid Refuse Truck Case Study with Miami-Dade County

In-service vehicle data collection from hydraulic hybrid vehicles (HHVs) and conventional vehicles was completed, including over 34,000 miles of 1-Hz automated side loader refuse truck driving data. The Commercial Vehicle Technologies team performed preliminary analysis of vehicle operation and performance of conventional diesels and both first-generation (model year 2013) and second-generation (MY 2015) hydraulic hybrids.

In FY 2017, NREL's Commercial Vehicle Technologies team completed chassis dynamometer testing of a diesel HHV at NREL's ReFUEL laboratory (see Figure VI.5-5). Data from dynamometer testing showed that the hydraulic hybrid system had higher fuel economy on drive cycles where the stops per mile are high, which is typical for residential refuse pickup. Testing also showed an increase in NO_x emissions from the hybrid vehicle. Further work to improve the hybrid controller may mitigate these increased emissions. Testing also shows evidence of Parker Hannifin's stated improved efficiency due to quicker acceleration rates for a given level of fuel consumption.



Figure VI.5-5 - Parker Hannifin CNG refuse truck with RunWise hydraulic hybrid system on NREL's Heavy-duty chassis dynamometer (Photo: NREL 38576)

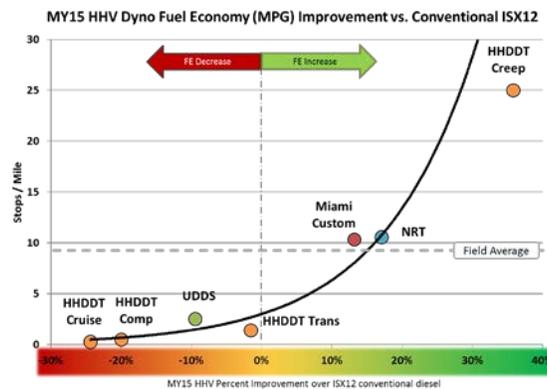


Figure VI.5-6 - Fuel economy improvement vs. stops/mile for a MY 2015 hydraulic hybrid. Average results for each drive cycle tested on the NREL ReFUEL chassis dynamometer.

Fleet DNA

Fleet DNA is NREL's central repository and clearinghouse of commercial fleet vehicle operating data that provide duty cycle data to vehicle manufacturers and developers to optimize energy efficient vehicle designs and help fleet managers choose appropriate technologies for their fleets. This online tool provides data summaries and visualizations similar to real-world "genetics" for medium- and heavy-duty commercial fleet vehicles operating in a variety of vocations. In 2017, the Fleet DNA database has grown to over 12 million miles of 1-Hz engine CAN, GPS, and component data from 1,700 vocational vehicles operated by fleet partners—UPS, FedEx, Coke, Frito-Lay, Foothill Transit, PG&E, Verizon, Walmart, Waste Management, Port of Long Beach, and more. Fleet DNA now includes over 4.5 million miles of 1-Hz electric vehicle and electric drive component data from commercial plug-in electric vehicles in real-world applications, including urban delivery, transit bus, electric utility truck, school bus, shuttle, and port drayage. NREL plug-in electric vehicle time-series data includes battery and electric motor currents, voltages, and temperatures along with data vehicle duty cycles, ambient conditions, charging profiles, and facility electrical demands. The Vehicle Technology Evaluation projects have helped populate the Fleet DNA database and establish Fleet DNA as a national resource for detailed commercial vehicle data. In the past year, NREL developed and used scientific

computing capabilities including multi-variate data analysis, data fusion, and visualization techniques - such as principal component analysis and hierarchical clustering with Fleet DNA data to assist industry and research partners in including seven DOE-awarded industry projects vehicle electrification, Super Truck II awards, and an ARPAe NEXTCAR award. Fleet evaluation data and analysis is also being used in partnership with other Federal and State agencies, including EPA, U.S. Department of Transportation (DOT), National Park Service, California Air Resource Board, California Energy Commission, and the South Coast Air Quality Management District.

Conclusions

NREL MD and HD vehicle technology evaluations provide test results, detailed on-road performance data, analysis, and published reports that help drive design improvements, guide deployment decisions, inform regulatory processes, and provide field data for researchers.

- Published 16 technical papers/presentations from fleet evaluation activities, including at key forums such as SAE Commercial Vehicle Engineering Congress, SAE World Congress, SAE Range Extenders Symposium, IEEE Transportation Electrification Conference, Electric Vehicle Symposium & Exhibition EVS29, Automate Vehicles Symposium and NTEA Green Truck Summit
- Published final technical report on Frito-Lay EV evaluation – and completed data collection and analysis activities on Foothill Transit EV bus, Miami-Dade HHV refuse hauler evaluations;
- Applied results of fleet evaluations and Fleet DNA to DOE research programs, including Energy Storage, Hydrogen and Fuel Cells, Power Electronics, National Clean Fleet Partnership, Clean Cities National Parks, Super Truck II, and EV Everywhere
- Fleet evaluation data and analysis are contributing to seven industry-led FOA vehicle electrification, Super Truck II awards, and an ARPAe NEXTCAR award
- Fleet evaluation data and analysis used by other Federal and State agencies, including EPA, U.S. Department of Transportation (DOT), National Park Service, California Air Resource Board, California Energy Commission, and the South Coast Air Quality Management District.

Key Publications

1. Prohaska, Robert, Simpson, Mike, Ragatz, Adam, Kelly, Kenneth, Smith, Kandler, and Walkowicz, Kevin. Field Evaluation of Medium-Duty Plug-in Electric Delivery Trucks (2016). <http://www.nrel.gov/docs/fy17osti/66382.pdf>
2. Eudy, L., R. Prohaska, K. Kelly, and M. Post. Foothill Transit Battery Electric Bus Demonstration Results. NREL/TP-5400-65274. January 2016. <http://www.nrel.gov/docs/fy16osti/65274.pdf>
3. Meintz, Andrew, Prohaska, Robert, Konan, Arnaud, Ragatz, Adam, Markel, Tony, and Kelly, Ken. Analysis of In-Route Wireless Charging for the Shuttle System at Zion National Park (2016). Web. <https://doi.org/10.1109/WoW.2016.7772090>
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5. Prohaska, Robert, Konan, Arnaud, Kelly, Kenneth, and Lammert, Michael. Heavy-Duty Vehicle Port Drayage Drive Cycle Characterization and Development: Preprint (2016). <http://www.nrel.gov/docs/fy16osti/66649.pdf>
6. Wang, Lijuan, Duran, Adam, Kelly, Kenneth, Konan, Arnaud, Lammert, Michael, and Prohaska, Robert. The Evaluation of the Impact of New Technologies for Different Powertrain Medium-Duty

Trucks on Fuel Consumption. SAE Technical Paper 2016-01-8134 (2016).

<http://dx.doi.org/10.4271/2016-01-8134>

7. Kast, James, Marcinkoski, Jason, Vijayagopal, Ram, and Duran, Adam. "Driving an Industry: Medium and Heavy Duty Fuel Cell Electric Truck Component Sizing." *World Electric Vehicle Journal* 8.1 (2016): 78-89.
8. Muratori, Matteo, Holden, Jacob, Lammert, Michael, Duran, Adam, Young, Stanley, and Gonder, Jeffrey. Potentials for Platooning in U.S. Highway Freight Transport: Preprint (2017).
<http://www.nrel.gov/docs/fy17osti/67618.pdf>

VII. Advanced R&D Projects

VII.1 Energy Impact of Connected and Automated Vehicle Technologies [DE-EE0007212]

Huei Peng, Principal Investigator

University of Michigan
G036 Lay Auto Lab.,
Ann Arbor, MI 48109-2133
Phone: (734) 769-6553
E-mail: hpeng@umich.edu

David Anderson, Program Manager

U.S. Department of Energy
Phone: (202) 587-5688
E-mail: David.Anderson@ee.doe.gov

Start Date: October 1, 2015	End Date: December 31, 2018	
Total Project Cost: \$2,970,197	DOE share: \$2,673,096	Non-DOE share: \$297,101

Project Introduction

Modern vehicles can generate tens to hundreds of GB of data every hour. Much of the utility of connected vehicle technologies lies in the potential value of this vast amount of data, including vehicle internal states, geographic road features, traffic flow and density, and individual vehicle movements, some of which are now available in separated repositories. The confluence of connected mobility data and emerging big data analytics presents both a challenge and an opportunity. The available data is then used to better understand driver behavior, energy and carbon emission, and traffic dynamics. For this project, data have been collected to (1) develop behavioral models representing how drivers react to information they are provided, (2) validate the traffic flow simulation model of Ann Arbor developed in POLARIS and (3) develop new driver model for Autonomie (e.g., how do drivers react to traffic signal information projected on a screen).

Another current trend in the industry is the rapid development of automated vehicle technologies. Recent breakthroughs in sensors, perception, and control technologies make vehicle automation much closer to reality. Almost all major OEMs and first tier suppliers have active programs for Connected and Automated Vehicles (CAVs). Many of them have aggressively target dates to bring their concepts to the market. While many research activities have occurred in the US over the past couple of years, the vast majority of those projects have been focused on safety rather than on energy and mobility.

The University of Michigan (UM) researchers have extensive experience equipping vehicles, collecting data, and analyzing the data to gain insight, or build models to understand various aspects of the transportation systems. The UM researchers will lead the experimentation part of this project, equipping 500 vehicles with ODB-port dongles to collect vehicle velocity and fuel consumption information.

The experimental data has been collected and used to develop and calibrate an open-source transportation network models POLARIS, which can be used in coordination with a more detailed energy simulation tool Autonomie to simulate the vehicles driving in the City of Ann Arbor traffic. The calibrated fuel consumption model has been used to develop and implement energy-saving concepts such as eco-routing, and adaptive traffic signal control for congestion reduction and energy saving. The learning experience can be extrapolated to other cities if data can be collected, model re-calibrated, and the control concepts adapted to the new transportation system.

Objectives

The objective of the project is to study the energy impacts of connected and automated vehicle technologies for a wide range of use cases and technology scenarios using both test data and high fidelity models. The project will evaluate the impact of a fast emerging technology on the energy benefit of current and future vehicle technologies through test data currently not available and by providing guidance for future R&D directions (i.e., component requirements, operating conditions) through the use of simulation tools.

Approach

This project consists of five inter-connected tasks, involving close-collaboration between the University of Michigan, the Argonne National Lab, and the Idaho National Lab. The approach of these five tasks are described below

- Task 1 Instrumentation and data acquisition of energy related information
 - Define candidate vehicle signals to be collected for energy purposes
 - Outfit 500 vehicles with the ODB-II logger, validation of the system – including the backhaul – and maintaining operations
 - Provide data to researchers in other Tasks of this project for model/control development
- Task 2 Display energy related information to study its influence on the driver
 - Identify CAV user functions, co-design and prioritize signals
 - Develop driver information display hardware and communication.
 - Design vehicle information display screen(s) and experimental cases
 - Review human test results. Review the field performance of the designed user interface
- Task 3 Travel Behavior Modeling
 - Experiment and survey design for travel behavior model
 - Model departure-time choice behavior
 - Model route choice behavior
 - Model travel activity pattern change
 - Calibration of POLARIS traveler behavior model
- Task 4 System Model Development and Validation
 - Develop the Ann Arbor and Ypsilanti region baseline POLARIS model
 - Determine data needs for further model development
 - Query, collect and process data from the connected vehicle fleet
 - Implement traveler and CAV agent behavior rules
- Task 5 Adaptive Signal Control
 - Build and calibrate the traffic simulation environment for the adaptive traffic signal control

- Develop the adaptive signal control algorithm
- Deploy and conduct field experiment at MCity and the Plymouth Road corridor
- Evaluate the energy saving of adaptive signal control.

Results

The results of the five tasks of this project are described below

- Task 1 Instrumentation and data acquisition of energy related information
 - COTS loggers using the OBD-II port and custom configurations to collect CAN bus data. The data being collected include PS position, vehicle speed, engine RPM, Mass air flow, fuel rate, absolute load, fuel trim for ICE vehicles, and for PHEV and EV, additional signals are collected: odometer, ambient temperature, AC power, heater power, battery SOC, battery current, and status of the vehicle (charging or driving)
 - Selected vendor Fleetcarma, acquired 500 units
 - Installation & data collection on vehicles ramping up; approximately 470 installed
 - System configures automatically to many vehicle models, including ICE, HEV, PHEV and EV types
 - Data collected and disseminated to UM, ANL and INL researchers
- Task 2 Display energy related information to study its influence on the driver
 - Identified CAV user functions, co-design and prioritize signals
 - Decisions on algorithms selection and the display hardware and communication based on intended content and availability
 - Acquired 10 ASD +antenna + DVI (Tablet) + Wifi Dongle + USB drive
 - Vehicle instrumentation and test in Mcity
- Task 3 Travel Behavior Modeling
 - A comprehensive literature review on activity-based travel demand modelling and the impact of AVs was conducted
 - Baseline activity model was developed using the Safety Pilot Model Deployment data
 - Studied ride-sharing opportunities
 - Defined similarity to quantitatively measure the extent to which travel activity patterns from two households are similar enough for AV sharing opportunity contractor

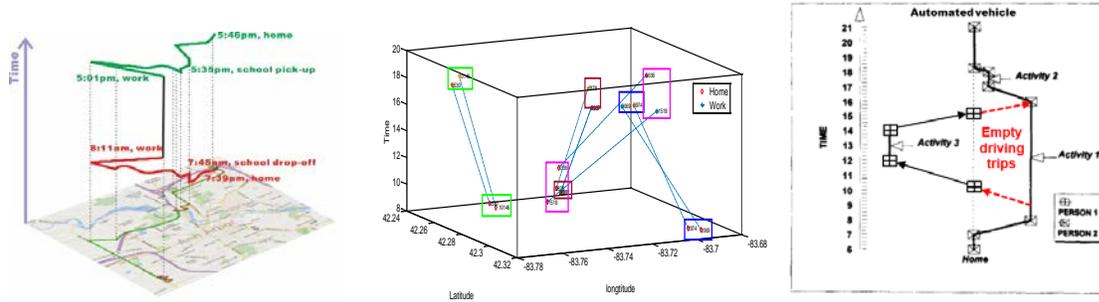


Figure VII.1-1 - Example time-space trajectory extracted from the Safety Pilot Model Deployment Database and AV sharing opportunity

- Task 4 System Model Development and Validation
 - Preliminary analysis of CACC impact
 - Simulation of CACC impact through parameter assumptions for value of travel time (VOTT), capacity changes and market penetration
 - Substantial changes in VMT/VHT at high penetration and low travel time value
 - Converted trips to OD flows and expand to represent travel in region for validation
 - Identified activity-travel pattern information
 - Appended imputed demographics to travel patterns
 - Synthesized activity-travel information and combine with SEMCOG survey
 - Developed framework for machine learning energy consumption model
 - Developed a fuel consumption model based on Ann Arbor trip information and Autonomie simulation model
 - The developed fuel consumption model was used to develop eco-routing algorithms to study the fuel-saving potential of this CAV function. Real-world case studies found that when the origin and destination of a trip are far away from each other enough, the following four routes can be very different: shortest, fastest, eco-routing (fuel economical), and eco-routing but with time-constraint (see Figure VII.1-2)
 - Implement and calibrate the POLARIS-Autonomie model (work in progress, see Figure VII.1-4)
- Task 5 Adaptive Signal Control
 - Developed a hardware-in-the-loop (HIL) simulation environment
 - A microscopic simulation model of 6 intersections on the Plymouth road of the city of Ann Arbor was constructed and calibrated
 - Generated surrogate basic safety messages (BSMs) from the simulation based on SAE J2735 standards

- o Designed and built the Connected Vehicle based Controller Interface Device (CVCID) to collect data from signal controllers, vehicle detectors and RSUs
- o Developed a traffic signal control algorithm based on vehicle trajectory estimation
- o Developed a spatiotemporal control algorithm
- o Developed an augmented reality technique which can be used to simulate Mcity or Plymouth road traffic conditions.

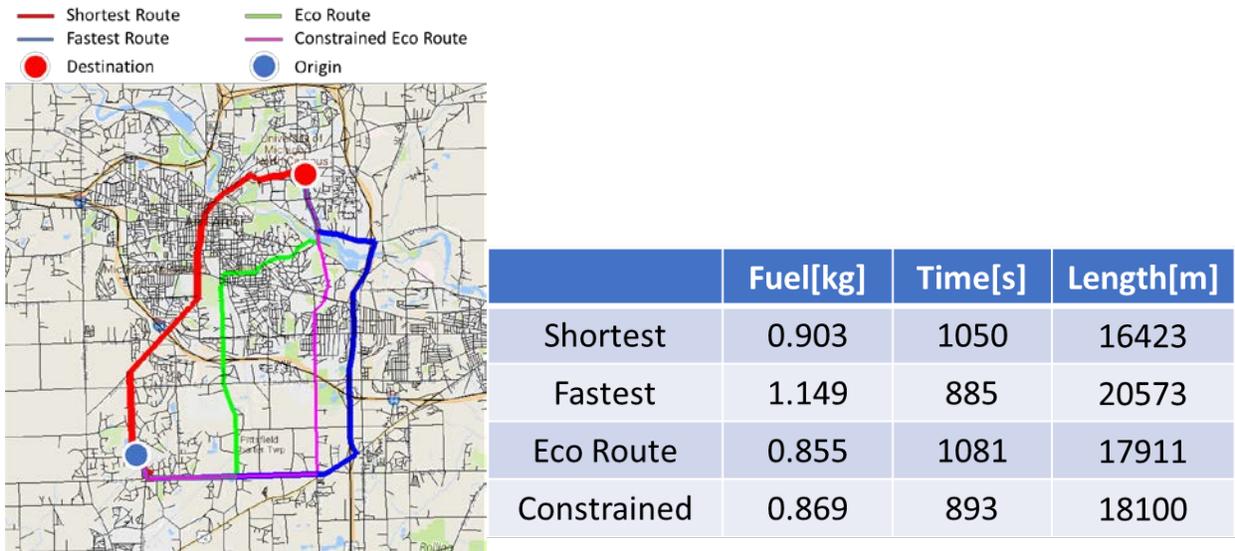


Figure VII.1-2 - Eco-routing results using Ann Arbor trip information, fuel economy model from the Autonomie model, and analysis of a pair of Ann Arbor Origin-Destination trip.

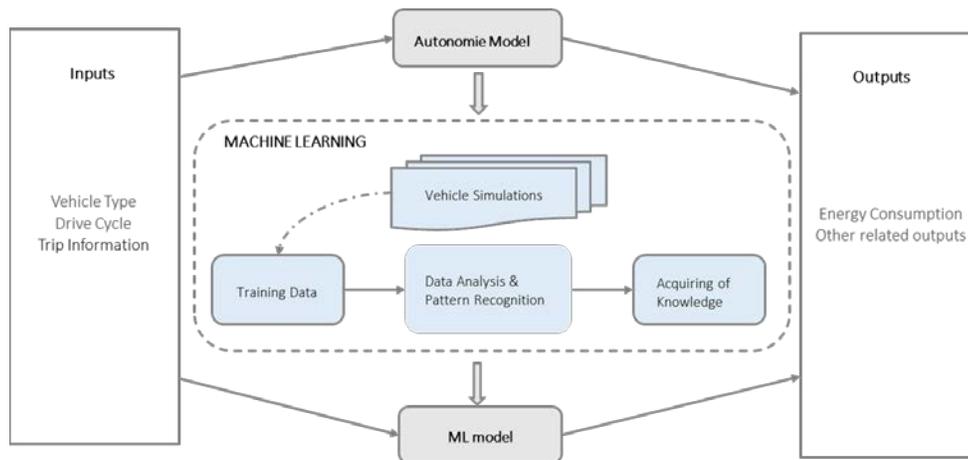


Figure VII.1-3 - Processing of developing the Ann Arbor Polaris Model.

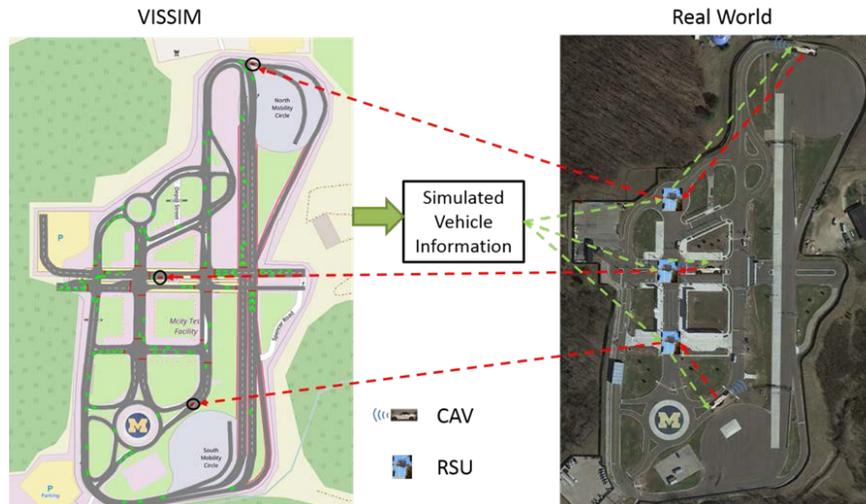


Figure VII.1-4 - Augmented reality technique developed to simulate CAVs in Mcity, which can also be used for traffic simulation in the city of Ann Arbor.

Conclusions

While there were much achievement over the past year, we also identified the following challenges:

- Data recording rate, fleet diversity, and CAN data decoding to generate useful data for the Polaris/Autonomie models
- Recruiting of volunteer drivers, especially regarding their “confidence of the OBD dongles”
- Interpreting the human behavior test results and incorporate into the POLARIS model took longer time than we originally anticipated
- Including Eco-Routing and Eco-AND models in POLARIS require addition of a microscopic simulation element, which add complexity and slows down the simulation significantly
- Implementing adaptive traffic control requires coordination from the City, which took longer time than we thought.

The major lessons learned and summary of this project include:

- OBD dongles are not as ready as we thought or as the vendors claimed.
- Volunteer recruiting was, and continue to be a challenge
- Despite of the challenges, ~ 460 dongles deployed
- Activity analysis provides possible framework for AV ride sharing algorithm development
- Eco-routing and Eco-AND models targeted for POLARIS integration
- Polaris is being converted to more accurately simulate the effect of CAV functions on energy consumption
- Adaptive traffic signal control algorithms developed, targeting deployment in 2017

Key Publications

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2. Feng, Y., Yu, C., Liu, H.X., Spatial-temporal Intersection Control in a Connected and Automated Vehicle Environment. *Transp. Res. Part C Emerg. Technol.* (3rd round review)
3. Yu, C., Feng, Y., Liu, H.X., Lane-based integrated optimization of traffic signals and vehicle trajectories at isolated urban intersections. *Transp. Res. Part B Methodological.* (2nd round review)
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