

Energy Efficient Mobility Systems

2018 Annual Progress Report

Vehicle Technologies Office

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Acronyms

A

AADT	Average Annual Daily Traffic
AC	Alternating Current
ACC	Adaptive Cruise Control
accel	Acceleration
ACES	Automated, Connected, Efficient Shared Mobility
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
ATDM	Active Transportation Demand Management
ATW	Active Transmission Warm up
AVTE	Advanced Vehicle Testing and Evaluation

B

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

C

CAC	Charge Air Cooler
CACC	Cooperative Adaptive Cruise Control
CAE	Computer-Aided Engineering
CAEV	Connected and automated electric vehicles
CAFE	Corporate Average Fuel Economy
CAN	Controller Area Network
CAV	Connected and automated vehicles
CARB	California Air Resources Board

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
CH ₄	Methane
CHTS	California Household Travel Survey
CRHTI	Chicago Regional Household Travel Inventory
CIP	Common Integration Platform
CMAP	Chicago Metropolitan Agency for Planning
Cm ³	Cubic
CNG	Compressed Natural Gas
CO	Carbon monoxide
CO ₂	Carbon Dioxide
COMM	Commuter
Conv	Conventional Vehicle
COP	Coefficient of Performance
CPT	Cumulative prospect theory
CRADA	Cooperative Research and Development Agreement
CS	Charge Sustaining
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
GGE	Gasoline gallon equivalent
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
MEP	Mobility energy productivity (MEP)
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,	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
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	
R2	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-	Random-Thresholds, Random-Parameters Hierarchical Ordered Probit
RWDC	Real-World Drive-Cycle
S	
S	Apparent power
SAE	Society of Automotive Engineers
SAV	Shared Automated Vehicles
SCAG	Southern California Association of Governments
SCAQMD	South Coast Air Quality Management District
SCIG	Southern California International Gateway
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
SPRINGS	Statistical Planning for Resilience in Next Generation Systems
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.	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
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 2018 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 four of the five EEMS activity areas: (1) the SMART (Systems and Modeling for Accelerated Research in Transportation) Mobility Lab Consortium, (2) High Performance Computing and Big Data Solutions for Mobility Data, (3) Advanced R&D Projects conducted by industry and academia, and (4) Core Modeling, Simulation, and Evaluation. Similarly, the remaining EEMS activity area – (5) Living Labs (managed under VTO's Technology Integration Program). Each of the individual progress reports provide a project overview and highlights of the technical results.

Table of Contents

Vehicle Technologies Office Overview	1
Organization Chart	1
Energy Efficient Mobility Systems Program Overview.....	2
Introduction	2
Mission and Goals	2
Program Organization	3
Research Highlights	7
I SMART Mobility- Advanced Fueling Infrastructure (AFI)	14
I.1 National Energy Impact of Electrified Ride-hailing Vehicles with Varying Infrastructure Support (ANL, NREL, ORNL)	14
I.2 Fuel Selection of Human-Driven Ride-Hailing Vehicles (INL) [Task 2.1]	21
I.3 Fuel Selection in Automated Mobility Districts – Dynamic Wireless Power Transfer (DWPT) Feasibility Analysis (ORNL, NREL) [Task 2.2]	25
I.4 Fuel Selection for Fully Automated Commercially Owned Taxi Fleet (LBNL/INL) [Task 2.3]	32
II SMART Mobility- Connected and Autonomous Vehicles (CAVS).....	39
II.1 Aggregation Methods to Estimate National-Level Impacts of CAVs Scenarios (ANL, NREL, ORNL) [Task 2B]	39
II.2 Traffic Microsimulation of Energy Impacts of CAV Concepts at Various Market Penetrations (LBNL) [Task 7A.1.2.]	45
II.3 Impact of CAVs on Energy, GHG, and Mobility in a Metropolitan Area (ANL) [Task 7A.1.3].....	59
II.4 Modeling CAVs transition dynamics and identifying tipping points (NREL) [Task 7A.1.4].....	66
II.5 Multi-scale, multi-scenario assessment of system optimization opportunities due to vehicle connectivity and automation – (ORNL) [Task 2.1]	72
II.6 Multi-Scale, multi-scenario assessment of system optimization opportunities due to vehicle connectivity and automation (ANL) [Task 7A.2.1.1]	79
II.7 Truck CACC operation at signalized intersections (LBNL) [Task 7A.3.1: Part I]	85
II.8 CACC Development for Passenger Cars with Different Powertrains (LBNL) [Task 7A.3.1 Part II].....	92
II.9 Experimental Evaluation of Eco-Driving Strategies (LBNL) [Task 7A.3.2]	97
II.10 Understanding CAVs in Automated Mobility Districts (INL, NREL) [Task 3.3.2]	102
II.11 Focused Validation of Select SMART Simulation Activities (ANL) [Task 7A.3.4]	105
III SMART Mobility - Mobility Decision Science (MDS)	111
III.1 WholeTraveler Study (LBNL, NREL, INL) [Task 1.0]	111
III.2 MA3T-MC on Market Dynamics Analysis	118
III.3 Mobility Behavioral Responses to Transportation Network Companies (NREL, LBNL) [Task 2.2]	124
III.4 Mobility Behavior and System Energy Efficiency: Plug-in Electric Vehicle Benefits Analysis (LBNL) [Task 3.1].....	128
III.5 Travel Behavior Simulation Modeling – POLARIS [Task 3.2]	135

IV SMART Mobility - Multimodal Transportation (MM)	142
IV.1 Enhance Existing Models to Estimate Impact of Modal Shifts; Intracity Passenger Travel (ANL) [Task 1.3].....	142
IV.2 Impact of Shared Mobility Use on Public Transit Services and Urban Form (LBNL, INL) [Task 1.4]	148
IV.3 Energy Analysis and Optimization of Multi-Modal Inter-City Freight Movement (NREL, ANL, INL) [Task 2.1].....	154
IV.4 Optimization of Intra-City Freight Movement with New Delivery Methods (ORNL, INL, NREL) [Task 3.1]	164
V SMART Mobility - Urban Science (US)	172
V.1 SMART Mobility Data and Models Informing Smart Cities (NREL, INL) [Task 2.1.1]	172
V.2 Mobility Energy Productivity Metric (NREL) [Task 2.1.2].....	178
V.3 SMART Mobility Modeling for Typical Mid-Size City [Task 2.1.3] (NREL).....	183
V.4 Coupling Land Use Models and Network Flow Models (LBL) [Task 2.2.2].....	189
V.5 Resilience for Electrified Vehicles and Automated Mobility Districts (LANL, INL) [Task 2.2.3].....	194
V.6 Infrastructure Spatial Sensing at Intersections (LIDAR) [Task 2.3.6] (NREL, ANL).....	201
V.7 Assessing Urban Impact: Automated Mobility Districts (NREL) [Task 2.4.1]	206
V.8 Smart urban signal infrastructure and control (ORNL, PNNL) [Task 4.1]	212
VI High Performance Computing and Big Data	219
VI.1 Reinforcement Learning-based Traffic Control to Optimize Energy Usage and Throughput (ORNL).....	219
VI.2 High Performance Computing for Mobility (HPC4Mobility) (LBNL).....	225
VI.3 Big Data Solutions for Mobility (LBL, ANL, PNL, ORNL)	231
VII Advanced Research and Development]	238
VII.1 Energy Impact of Connected and Automated Vehicle Technologies [DE-EE0007212].....	238
VII.2 Boosting Energy Efficiency of Heterogeneous Connected and Automated Vehicle (CAV) Fleets via Anticipative and Cooperative Vehicle Guidance (Clemson University)	243
VII.3 Developing an Eco-Cooperative Automated Control System (Eco-CAC).....	254
VII.4 Evaluating Energy Efficiency Opportunities from Connected and Automated Vehicle Deployments Coupled with Shared Mobility in California (UCR/NREL)	260
VIII Core Modeling, Simulation, and Evaluation	267
VIII.1 Vehicle Systems and Mobility Research (ANL).....	267
VIII.2 Core Modeling: Maintenance; Tools; Real World Energy Impact Estimation; and Toyota Prius Prime Validation (ANL).....	275
VIII.2.1 Maintenance.....	275
VIII.2.2 Core Modeling Tools.....	276
VIII.2.3 Real-World Energy Impact Estimation.....	278
VIII.2.4 Toyota Prius Prime Validation	281
VIII.3 Modeling, Simulation, and Data Analysis (NREL).....	285

List of Figures

Figure-1 Total Operational Cost Comparison between ICEV and EV fleets	7
Figure-3 Focused Validation of Select SMART Simulation Activities -Summary of the relative fuel and energy consumption of approach strategies 2 and 3 compared to approach 1 for Situation 2	8
Figure-4 - Simulated intersection and actuated control parameters	9
Figure-6 - Modal shares for the Base San Francisco Bay Area scenario and three sets of variations with cost of modes shifted +/-50% (for gasoline and transit) or +/-25% (for ride hail).	10
Figure-7 – Energy consumption rate for baseline and alternative freight delivery scenarios	10
Figure-8 - Energy Impact of Electrified Class 7&8 Electric Truck in the United States (500-mi electric range).....	11
Figure-9 - MEP 2.0 methodology applied to: a) Austin, TX; b) Columbus, OH; c) Denver, CO	11
Figure-10 - . GRIDSMART capture labeled the ground imager data as a “Ford Transit Connect,” which has an estimated fuel efficiency of 28 MPG.	11
Figure-11 – Flow Impact due to Different Optimization Solutions: Time-Based User Equilibrium (UET); Time-Based System Optimal (SET); Fuel-Based User Equilibrium (UEF); Fuel-Based System Optimal (SEF)	12
Figure-12 – Real-world Energy Impact Estimation Approach Overview.....	12
Figure I.1.3 BEV Market penetrations with different levels of infrastructure support.....	18
Figure I.2.1 Five-year cost of ownership for a full-time ride-hailing driver by cost component for each vehicle type, assuming driver has access to home charging.....	23
Figure I.3.1 Block diagram of a typical track-based DWPT system.....	27
Figure I.3.2 An example of a DWPT system using paralleled short sectional 100 kW primary couplers and arrays of pickup couplers. As displayed, the light-duty vehicle is receiving 200 kW and the heavy-duty vehicle is receiving 600 kW.	28
Figure I.3.3 Vehicle energy consumption levels at different constant travel speeds.	29
Figure I.3.4 DWPT coverage assessment for 100 miles of sustained constant speed traveling (drivetrain power only).	29
Figure I.3.6 Airgap field distribution for the 100kW DWPT system deployment.....	30
Figure I.3.7 Variation of track-to-vehicle mutual inductance with respect to vehicle position.	30
Figure I.3.8 Pareto solutions from the optimization model for two different cases (LDC only and LDV and HDV together)	30
Figure I.4.1 Charging Station Planning Based on Nodal Demands	33
Figure I.4.2 Number of charging demands in different cases	34
Figure I.4.3 Number of chargers in different cases.....	34
Figure I.4.4 Number of charging stations in different cases	35
Figure I.4.5 Illustrative examples of charging station locations	35
Figure I.4.6 Relationships of SOC, charge duration, and temperature	36
Figure I.4.6 Total operation cost comparison between ICEV and EV fleets.....	37
Figure II.1.2 Projected personal vehicle sales (a), and projected passenger-miles traveled by the primary mode of household (HH) travel (b)	42
Figure II.1.1 Components of consumer utility modeled in MA3T-MC in years 2035 (a) and 2050 (b)	42
Figure II.2.1 Simulation showed that low market penetration (< 40%) of CACC vehicles caused fuel consumption increase than the status quo traffic (without CACC vehicles).....	46
Figure II.2.2 energy consumption rates for heavy duty trucks	49

Figure II.2.3 Simulated intersection and actuated control parameters 51

.Figure II.2.4 Average vehicle speed under various CACC market penetrations 52

Figure II.2.5 Average vehicle mpg under various CACC market penetrations. 52

Figure II.2.6 Performance of the signal control algorithm in the 40% CACC case..... 53

Figure II.2.7 Performance of the signal control algorithm in the 100% CACC case..... 53

Figure II.2.8 Road Geometry for microscopic traffic simulation: I-66 EB inside the Beltway;
with two bottlenecks marked with Red Spots 55

Figure II.3.1 POLARIS modeling process with CAV improvements highlighted 60

Figure II.3.2 Scenario design for Bloomington case studies 61

Figure II.3.3 Best and worst case performance metrics over time under privately owned,
Level 4/5 CAV scenarios 62

Figure II.3.4 Flow-Density Relationship for M=45..... 64

Figure I.3.5 NFD analysis for the Bloomington, Illinois, model 64

Figure II.4.1 Summary of the frequency of different bottlenecks to CAV adoption among the
scenarios. Proportions of results in the figure should not be interpreted as probabilities of
outcomes because input assumptions do not include probability distributions. (Source: NREL.) 68

Figure II.4.2 Fuel-consumption outcomes for scenarios in the screening study. Each corner of the
triangle represents a “pure” Level 0, Level 1, or Level 4 vehicle fleet and points in between those
corners represent outcomes with mixes of those vehicle types. (Source: NREL.) 69

Figure II.4.3 Regression tree showing major influences on energy consumption. Each pie chart
shows the fraction of results that lie in the best 5% of fuel consumption within simulations
selected by the preceding branching criterion. (Source: NREL.) 69

Figure II.4.4 Distribution of energy outcomes for scenarios, distinguished by the predominance
of L4 CAVs in the scenarios. (Source: NREL.)..... 70

Figure II.4.5 Comparison of fuel consumption vs. total vehicle miles traveled (VMT) in energy
sensitivity analysis (each point represents one of the simulations from the energy sensitivity study)
relative to multi-lab study scenarios (lines and shaded ranges) as reported in Stephens *et al.* 70

Figure II.4.6 A traveler’s utility is calculated for each simulation as a function of capital and operating
costs for travel, the time taken, vehicle occupancy, and demand for travel. Each point in the figure
is the value of average utility of travelers versus fuel consumption in a single simulation. The left
panel shows simulations with Level 4 adoption below 20%; the right panel shows those with Level 4
adoption above 20%. Travelers prefer higher utilities to lower ones..... 71

Figure II.5.1 Fuel/Power consumption estimation process (left), curve fitting for a medium duty
vehicle (right)..... 73

Figure II.5.2 Simulation scenario - highway corridor..... 74

Figure II.5.3 Simulation results - highway corridor..... 74

Figure II.5.4 Simulation scenario - urban corridor 75

Figure II.5.5 Accumulated fuel consumption per vehicle along the corridor 76

Figure II.5.6 Simulation results - urban corridor 76

Figure II.5.7 Spatial-temporal distribution of mean speed plots of main and ramp roads
(Black lines indicate the start and end of the control and/or merging zones) 77

Figure II.6.1 RoadRunner workflow to simulate a CAV scenario..... 80

Figure II.6.2 Eco-approach impacts on the energy benefits of components 81

Figure II.6.3 CAV model validation on platooning scenario for middle (veh2, left) and trailing
(veh3, right) vehicle 82

Figure II.6.4 Electric vehicle travel between stops	83
Figure II.7.1 The Concept of Operation of Integrated CACC Trucks, real-time microscopic traffic simulation in Aimsun, and Active Traffic Signal Control.	87
Figure II.8.1 Overall CACC system structure.....	93
Figure II.8.2 Control System Structure.....	94
Figure II.8.3 Vehicles to be used	95
Figure II.9.1 Flowchart for Estimating Fuel Consumptions of Trips.....	100
Figure II.10.1 Power data from the two shuttle charging circuits over a 24-hr period is shown	103
Figure II.11.1 Intersection eco-approach and launch with no stop required (Situation 1).....	107
Figure II.11.2 Summary of the relative fuel and energy consumption for approach strategies 2 through 4 for Situation 1	107
Figure II.11.3 Intersection eco-approach with stop and idle required (Situation 2)	108
Figure II.11.4 Summary of the relative fuel and energy consumption of approach strategies 1 through 3 compared to cruising through the intersection without stopping for Situation 2.....	108
Figure II.11.5 Summary of the relative fuel and energy consumption of approach strategies 2 and 3 compared to approach 1 for Situation 2	109
Figure II.11.6 Loss of information due to decreased sampling rate.....	109
Figure III.1.1 Phase of diffusion and diffusion potential in the population by technology/service. Source: LBNL, NREL, and INL Joint Study).....	116
Figure III.2.1 Segmentation structure tree for modeling traveler heterogeneity.....	119
Figure III.2.2 Mobility choices in person miles traveled (PMT)	120
Figure III.2.3 Sales by vehicle technologies	121
Figure III.2.4 Disaggregate Consumer Choices of Vehicle and Mobility Technologies.....	122
Figure III.3.1 Low and high estimates of net energy impact of ride sourcing in Austin	126
Figure III.4.1 BEAM represents the road network, land use, parking infrastructure, charging infrastructure, transit system, traveler activities, personal mobility, and explicit vehicle movements.	129
Figure III.4.2 Value of travel time in the virtual population simulated in BEAM, disaggregated by annual household income (note that “200” in the figure contains all income above \$200k).....	130
Figure III.4.3 Household income distribution of the simulated population in BEAM.	131
Figure III.4.4 Modal shares for the Base San Francisco Bay Area scenario and three sets of variations with cost of modes shifted +/-50% (for gasoline and transit) or +/-25% (for ride hail).....	132
Figure III.4.5 System energy consumption for the Base San Francisco Bay Area scenario and three sets of variations with cost of modes shifted +/-50% (for gasoline and transit) or +/-25% (for ride hail). Percentage labels are all relative to the Base scenario.	132
Figure III.4.6 Modal share between a base scenario (equivalent to the scenario used for calibration except with reduced ride hail cost by 50%) and two scenarios where adoption of ride hail is limited according to the demographic distributions estimated from the Whole Traveler Behavioral Study. The AV Interest scenario simulates adoption by respondents who indicated interest with AV technology. The RH Use/Interest scenario includes respondents who indicated use of or interest in shared mobility (but with overall reduced uptake due to a lack of geographic specificity in application of the model results).....	133
Figure III.4.7 Total system energy consumption comparison between a base scenario (equivalent to the scenario used for calibration except with reduced ride hail cost by 50%) and two scenarios where adoption of ride hail is limited according to the demographic distributions estimated from the Whole Traveler Behavioral Study. The AV Interest scenario simulates adoption by respondents who indicated	

interest with AV technology. The RH Use/Interest scenario includes respondents who indicated use of or interest in shared mobility (but with overall reduced uptake due to a lack of geographic specificity in application of the model results). 133

Figure III.5.1 POLARIS modeling process with MDS improvements highlighted..... 136

Figure III.5.2 Key findings from activity start time choice model 137

Figure III.5.3 VMT sensitivity to changes in behavioral parameters..... 139

Figure III.5.4 Change in transit mode share from baseline to subsidized TNC access scenario 140

Figure IV.1.1 POLARIS Modeling Process with Multimodal Tasks Highlighted 143

Figure IV.1.2 Filtering Heuristics for Locations with no Feasible Walking Access to/from Transit..... 144

Figure IV.1.3 Flowchart for Multimodal Simulation..... 145

Figure IV.1.4 POLARIS to SVTriP..... 146

Figure IV.1.5 Histograms of (a) Passenger Miles per Gallon (left) and (b) Vehicle Miles per Gallon (right) 147

Figure IV.2.1 Map of Mode Shift and Vehicle Impacts in Washington DC due to car2go..... 151

Figure IV.2.2 Map of Mode Shift and Vehicle Impacts in San Diego due to car2go 152

Figure IV.3.1 - Price Comparison of Heavy Duty Trucks with Different Powertrain Technologies 156

Figure IV.3.2 - Simulated Truck Energy Consumption (kwh/mile) a 500-mile electric truck 157

Figure IV.3.3 - Electric Class 7&8 Truck Market Shares (500-mi electric range) 158

Figure IV.3.4 - Energy Impact of Electrified Class 7&8 Electric Truck in the United States (500-mi electric range)..... 158

Figure IV.3.5 - Model framework and workflow. 159

Figure IV.3.6 - Multimodal freight network topology and data 159

Figure IV.3.7 - Baseline Freight Volume Assignment of U.S. 160

Figure IV.3.8 Load Pooling Freight Volume Assignment of U.S. 161

Figure IV.3.9 National wide comparison between load pooling and baseline..... 162

Figure IV.4.1 TAZs with actual GPS stop counts (upper left), TAZs with estimated counts from model (upper right), and all TAZs within Franklin County, Ohio with stop counts (center) (in ArcGIS) 165

Figure IV.4.2 Energy consumption for different portions of a one-minute hover test reflect higher energy use as weights and flight times increase 166

Figure IV.4.3 -Energy consumption at one-minute flight test with different speeds and weights..... 167

Figure IV.4.4 Energy consumption rate (kwh/mile) for baseline and alternative scenarios 169

Figure IV.4.5 Energy consumption at one-minute flight test with different speeds and weights. Larger packages are comparable in energy use to an electric passenger car 170

Figure V.1.1. Airport Passengers at Four Cities of Focus (Source: NREL working paper) 174

Figure V.1.2 Comparison of Interest in Alternative Fuel Vehicles by Generation (Source: Strategic Vision, 2018)..... 176

Figure V.2.1 MEP metrics for Columbus, OH for: a) Car mode; b) Walk, Bike, and Transit modes (combined); c) All modes 180

Figure V.2.2 MEP 2.0 methodology applied to: a) Austin, TX; b) Columbus, OH; c) Denver, CO..... 181

Figure V.3.1 ODOT/MORPC ABM-DTA Modeled Network (Source: Ohio Department of Transportation)..... 186

Figure V.3.2 Current Mobility Challenges in Austin (Source: Austin Smart Mobility Report)..... 187

Figure V.4.1 Schematic of tightly coupled land use and travel models using 5-year cycles..... 190

Figure V.4.2 192

Figure V.6.1 Argonne National Laboratory proof of concept exploratory portable awareness system.....	203
Figure V.7.1 Conceptual depiction of AMDs	207
Figure V.7.2 AMD Toolkit – Workflow	208
Figure V.7.3 (a) A hypothetical AMD network in SUMO and (b) A zoom in on the network to show signals, sidewalk lanes and vehicles. [Green lines → Car mode; Yellow lines → Pedestrian mode; Red lines → AES mode].....	208
Figure V.7.4 A depiction of Greenville AMD network in SUMO	210
Figure V.8.1 Trade-off between Mobility and Energy for Different Penalty Values	214
Figure V.8.2 Target and Actual Queue Length PDFs for Static B-spline Model Based Control	215
Figure V.8.3 Response Plot of the Queue Length Dynamics for a Single Intersection Control.....	216
Figure V.8.4 Fault Diagnosis Results and the Guarantee of Safe Distance between Any Two CAVs.....	216
Figure VI.1.1 Data collection to estimate fuel consumption using GRIDSMA RT cameras. GRIDSMA RT installations at ORNL will be used in conjunction with a ground imaging system under development for another project. The simultaneous captures will be used to produce a library of images suitable for training a machine learning algorithm to estimate fuel consumption.	220
Figure VI.1.2 GRIDSMA RT capture (overview) with simultaneous ground imager collection (bottom left). The commercial application labeled the ground imager data as a “Ford Transit Connect,” which has an estimated fuel efficiency of 28 MPG. The bottom right depicts an image of the same vehicle, found independently, confirming this labeling. Using this and many more captures we can begin to teach the GRIDSMA RT cameras how to estimate vehicle fuel consumption.	222
Figure VI.1.3 Example of an actual tracked vehicle from the ORNL GRIDSMA RT camera. The image degradation due to resolution and the fish-eye lens is profound at longer distances and degrades classifier performance, as shown in Table I.1.1.....	223
Figure VI.2.1 LA Basin road link/intersection network	226
Figure VI.2.2 ETAP Approach Overview and Mathematical Formulas.....	227
Figure VI.2.3 Flow Impact Due to Different Optimization Solutions	228
Figure VI.2.4 Distance Impact on Travelers Due to Different Optimization Solutions: Normalized to User Equilibrium Travel Time.....	228
Figure VI.2.5 Difference in Vehicle Miles Traveled with respect to User Equilibrium Travel Time Optimization	229
Figure VI.2.6 Travel Time Impact with Respect to User Equilibrium Travel Time Optimization.....	229
Figure I.2.7 Bay Area Network with highlighted highest flow links for UET solution.....	229
Figure VI.2.8 Metrics to Consider for Urban-Scale Fleet Level Optimization.....	230
Figure VI.3.1 TCN Architectural Elements.....	234
Figure VI.3.3 Comparison of Total energy consumption by trip generated by Autonomie and CART clusters	236
Figure VII.2.1 The project breakdown into three main objectives.	244
Figure VII.2.2 Block diagram of the major motion planning algorithm components.	245
Figure VII.2.3 Functional architecture of the developed iOS OBD Logger App [7-8].	246
Figure VII.2.4 <i>The wireless communication simulator</i>	246
Figure VII.2.5 Position prediction errors in the Tiger Commute bus dataset.	247
Figure VII.2.6 Fuel economy benefits of CAVs in multi-agent mixed traffic MATLAB simulations.....	247
Figure VII.2.7 Scenario 1 trajectory, velocity, lane decision variable, and acceleration plots.	248
Figure VII.2.8 Vissim with multiple MPC vehicles (orange), and human controlled traffic (black)	248
Figure VII.2.9 Retrofitted Vehicles by Self-Developed Robotic AutoDrive System.....	248

Figure VII.2.10 Performance of (a-b) speed tracking and (c) trajectory tracking controllers 249

Figure VII.2.11 *Physical vehicle embedded in virtual Vissim environment.* 249

Figure VII.2.12 (a) Our road-side unit (RSU) for DSRC (b) the RSU box powered by solar panels at test track (c) the direct antenna communicating with the RSUs at the test track. 250

Figure VII.2.13 Impact of path loss on PDR and reliability for T-window=300msec. 251

Figure VII.2.14 Impact of path loss model on PDR and reliability with T-window=1sec. 251

Figure VII.2.15 Per received packet/instance latency..... 252

Figure VII.3.1 Proposed Eco-CAC system..... 255

Figure VII.3.2 HEV fuel consumption estimation 256

Figure VII.3.3 NFD for the protected network — fixed plan (FT), phase split (PS), phase split with cycle length (PSC), gating (G)..... 257

Figure VII.3.4 BEV Eco-CACC-I results at 40 mph 258

Figure VII.3.5 Energy consumption of the eco-predictive control on Interstate-81 258

Figure VII.4.1 Model Framework..... 262

Figure VII.4.2 Datasets and major scenarios of CAV applications and experiments 263

Figure VIII.1.1 Experimental Setup for 2-Vehicle Aerodynamic Following Impacts Assessment..... 268

Figure VIII.1.2 Highlighted On-Road Driving Routes (left) and On-Road Experimental Vehicles (right) [clockwise from upper-left – BMW i3 ReX, Honda Accord PHEV, Toyota Prius PRIME PHEV, Ford Taurus IC vehicle] 268

Figure VIII.1.3 Highlighted Radar and Video Images from Vehicle-as-a-Sensor Preliminary Data Collection..... 269

Figure VIII.1.4 Highlighted Road-Load Force Reduction for Varying Vehicle Time Gaps and Speeds for 2-Vehicle Experiments..... 270

Figure VIII.1.5 Observed ACC Operational Envelopes for Two Select Study Vehicles 270

Figure VIII.1.6 Highlighted Robotic Driver Use Modifications and Use Cases 271

Figure VIII.1.7 Prius Prime ACC Target Following Time versus Vehicle Speed..... 272

Figure VIII.1.8 Laboratory Experiment Driving US06 with ACC MiM Active and Emulating a Lead Vehicle Following Prescribed Drive Trace..... 272

Figure VIII.1.9 Example Vehicle Speed and Sensed Gap Distances for Single Highway Run (from Argonne to Downtown Chicago) 273

Figure VIII.2.2.1 The Energy for Transportation Workflow 277

Figure VIII.2.3.1 Approach overview procedure..... 279

Figure VIII.2.3.2 Honda Civic fuel economy distribution..... 279

Figure VIII.2.3.3 Toyota Prius fuel economy prediction distribution vs Real world fuel economy distribution for various accessory loads..... 280

Figure VIII.2.4.1 Battery output power according to battery SOC..... 282

..... 282

Figure VIII.2.4.2 Vehicle wheel power operating points according to battery SOC..... 282

..... 283

Figure VIII.2.4.3 Battery output power according to the battery SOC..... 283

Figure VIII.2.4.4 Comparison of vehicle operating conditions (UDDS cycle, 22°C and -7°C ambient temperature) 283

Figure VIII.3.2 The TSDC’s public website, which underwent a major redesign in FY 2018, offers cleansed data for download while a secure portal provides approved users with access to spatial data. Credit: NREL 286

Figure VIII.3.1 The TSDC boasts a growing number of registrants from various backgrounds, primarily academia, government, and private industry. Credit: NREL 286

Figure VIII.3.3 Map showing freight volumes (red) along major U.S. roadways and Fleet DNA data coverage (blue) along those routes. Credit: NREL 286

Figure VIII.3.4 FASTSim validation efforts focus on price, acceleration, and fuel economy. Credit: NREL 286

List of Tables

Table 1 - Alignment of EEMS Activities with Strategic Goals	5
Table I.2.1 RideAustin driver segmentation statistics	22
Table I.3.1 Example 100kW dynamic WPT secondary coil parameters for a roadway embedded ferrite track.	30
Table I.4.1 BEAM Output Metrics for San Francisco Bay Area Cases – PEV Taxis With 80% Service Level	37
Table II.2.1 Speed Bin Definition for MOVES Model: Determination of operating modes	49
Table II.2.2 Regression Coefficients in the Calibrated Model.....	54
Table II.2.3 Averaged performance parameters for each market penetration level of ACC vehicles over 10 replications (random seeds)	55
Table II.3.1 Comparison to baseline for Levels 4 and 5 CAVs for various fleet assumptions	62
Table II.3.2 Bloomington, Illinois, mobility and energy impacts resulting from platooning	63
Table II.4.1 Hypotheses	67
Table II.5.1. Loss of accuracy for a medium duty vehicle.....	73
Table II.5.2 Summary of traffic scenarios	75
Table II.6.1 Comparison of fuel economy and travel time by controllers	83
Table II.7.1 Root Mean Square and Maximum of tracking errors.....	88
Table II.7.2 Cut-in Maneuvers: Root Mean Square and Maximum of tracking errors.....	89
Table II.7.3 Truck Speed Variation between 55 ~ 65 mph.....	90
Table II.10.1 Operational Data Details – July 17, 2018.....	103
TABLE II.11.1 Test Vehicle Specifications	106
Table III.1.1 The Effect of Transitions between Family Stages on Mode Use Behavior	117
Table III.3.1 TNC Energy Framework, Potential Impacts.....	127
Table III.4.1 Technology diffusion scenarios used for analysis.	131
Table I.5.1 Home-based Value of Time by Income Level.....	137
Table-III.5.2 Transit Access Scenario Mobility and Energy Results.....	139
Table IV.3.1 Performance Characteristics of Existing and Future Electric Trucks	156
Table IV.3.2 Baseline Modal Share of U.S.....	160
Table IV.3.3 Loading Pooling Modal Share of U.S.....	161
Table IV.4.1 Energy estimates for baseline and alternative scenarios.....	168
Table V.6.1 Energy equivalence of safety summary – DRAFT ESTIMATES/RESULTS	203
Table V.8.1 Statistical Verification of Results	214
Table V.8.2 The Weights Matrix for the Static B-spline Queue Length PDF Model.....	215
Table VI.1.1 Estimates of Fuel Economy using CNN Baseline Model.....	222

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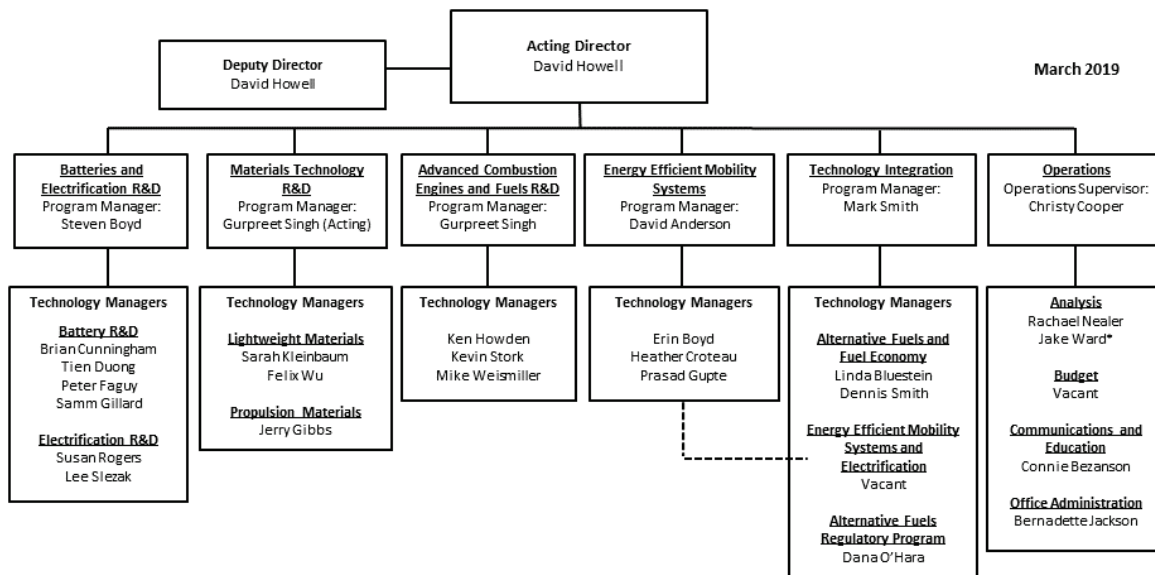
Vehicle Technologies Office Overview

Vehicles move our national economy. Annually, vehicles transport 11 billion tons of freight¹ – more than \$32 billion worth of goods each day² – and move people more than 3 trillion vehicle-miles.³ Growing our national economy requires transportation and transportation requires energy. The transportation sector accounts for 70% of U.S. petroleum use. The United States imports 20% of the petroleum consumed – sending more than \$15 billion per month⁴ overseas for crude oil. The average U.S. household spends nearly one-sixth of its total family expenditures on transportation⁵, making transportation the most expensive spending category after housing.

To strengthen national security, enable future economic growth, improve energy efficiency, and increase transportation energy affordability for Americans, the Vehicle Technologies Office (VTO) funds early-stage, high-risk research on innovative vehicle and transportation technologies. VTO leverages the unique capabilities of the national laboratory system and engages private sector partners to develop innovations in electrification, including advanced battery technologies; advanced combustion engines and fuels, including co-optimized systems; advanced materials for lighter-weight vehicle structures; more efficient powertrains; 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) that leverage relevant expertise. These partnerships 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 is too far from market realization to merit industry resources.

Organization Chart



¹ Bureau of Transportation Statistics, DOT, 2016. Table 3-1 Weight and Value of Shipments by Transportation Mode https://www.bts.gov/archive/publications/transportation_statistics_annual_report/2016/tables/ch3/table3_1

² Ibid.

³ Transportation Energy Data Book 37th Edition, ORNL, 2018. Table 3.8 Shares of Highway Vehicle-Miles Traveled by Vehicle Type, 1970-2016.

⁴ EIA Monthly Energy Review <https://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf>

⁵ Bureau of Labor Statistics, Consumer Expenditure Survey, 2017. Average annual expenditures and characteristics of all consumer units, 2013-2017. <https://www.bls.gov/cex/2017/standard/multiyr.pdf>

Energy Efficient Mobility Systems 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) 2018.

The introduction of disruptive transportation technologies and services, such as connected and automated vehicles, car-sharing, and ride-hailing services, provides new, low-cost mobility options for consumers. Additionally, the evolving retail sector, shaped by the convenience of online shopping, has resulted in not only a shift in how we transport and deliver goods, but it has also had ripple effects in personal transportation. This transforming mobility landscape presents a significant opportunity to improve economic and energy productivity and advance safety, affordability, and accessibility in the transportation sector.

While these changes in the transportation system can provide benefits to the American public, they also present risks, challenges, and questions 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, accessible, 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 2018 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.

During FY 2018, the EEMS Program developed a preliminary metric framework known as *mobility energy productivity*. Because EEMS aims not only to reduce the energy consumed in the transportation system, but also to reduce the time and cost associated with moving people and goods while improving access to mobility, a comprehensive metric that incorporates all four factors (energy, time, cost, and accessibility) is required. Mobility energy productivity (MEP) will be used as a lens through which the EEMS program can evaluate the mobility impacts that potential technologies and services may have, and by which program success can be measured as it develops new mobility solutions.

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

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

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

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

Program Organization

To achieve its programmatic goals, the EEMS Program implements 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
- Advanced R&D Projects
- Core Modeling, Simulation, and Evaluation
- Living Laboratories

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 Freight (MMF):** Reducing modality interface barriers for freight movement and understanding the interrelationships between various modes for both long-distance freight transport and last-mile goods delivery.
4. **Urban Science (US):** Evaluating the intersection of transportation networks and the built environment in terms of energy and mobility opportunities,
5. **Advanced Fueling Infrastructure (AFI):** Understanding the costs, benefits, and requirements for fueling and 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

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 efforts in this area include:

The HPC4Mobility initiative establishes small seedling projects that partner national lab capabilities with third parties who have access to data. The initiative is aimed at accelerating the discovery, design, and development of energy efficient mobility systems by enabling access to computational capabilities and data science expertise in the DOE laboratories. Projects selected under HPC4Mobility will reduce the time and cost required for mobility infrastructure planning and decision-making, and enable optimized control of intelligent transportation systems in real-time.

Additional projects within the Big Data portfolio support 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. These projects include multi-lab efforts focused on developing city/regional-scale "digital twins" of the transportation system, and applying deep-learning techniques to support the development of resilient automated vehicle control systems.

HPC4Mobility and Big Data 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 mobility improvements through advancements in hardware, software, control systems, advanced sensing and computing, 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.

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.

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.

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	▲	●	▲
Core VTO Tools	●	▲	▲
Living Laboratories	▲	▲	●

Coordination

The EEMS program coordinates its activities with the U.S. Department of Transportation (USDOT), industry stakeholders, and other members of the mobility research community.

Coordination between EEMS and the various modal administrations within USDOT is critically important due to the linkage between VTO's research and development activities to create efficient, secure, and sustainable transportation technologies, and USDOT's mission to ensure our nation has the safest, most efficient and modern transportation system in the world⁶. This coordination has allowed both agencies to gain mutual benefit from coordination between USDOT's Smart City Challenge and VTO's SMART Mobility Lab Consortium, and leverages each agency's technical expertise and previous experience in mobility related technologies. For example, through the Technology Integration program, VTO has supported a Technologist-in-Cities pilot, embedding a mobility energy expert within a USDOT-funded Smart City to facilitate data discovery, best practices sharing, and identification of critical transportation research that will directly benefit the 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 2018, U.S. DRIVE created a new Vehicle and Mobility Systems Analysis Technical Team (VMSATT), to identify the most promising areas of pre-competitive mobility research of interest to the government, automotive industry, energy sector, and utility company partners. Additionally, the EEMS Program coordinates with the medium- and heavy-duty trucking and freight industry through the 21st Century Truck Partnership (21CTP)ⁱ, by pursuing collaborative research and development to realize its vision for our nation's trucks and buses to safely and cost-effectively move larger volumes of freight and greater numbers of passengers while emitting little or no pollution⁷. The EEMS Program is directly involved with the Operational Efficiency Technical Team within the truck partnership.

The EEMS Program continually seeks additional high-value opportunities to engage with relevant stakeholders in order to share EEMS-funded research results and learn from other mobility-related efforts. For example, the EEMS Program is a governmental sponsor and member of the National Academies/Transportation Research Board Forum on Preparing for Automated Vehicles and Shared Mobility, which brings together public, private and other research organizational partners to share perspectives about how the deployment of automated vehicles and shared mobility services may dramatically increase safety, reduce congestion, improve access, enhance sustainability, and spur economic development⁸.

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.

The VTO Technology Integration Program funded and has primary management responsibility for Living Laboratories projects during FY 2018. Living Laboratories projects are not included in the FY2018 EEMS APR.

⁶ <https://www.energy.gov/eere/vehicles/21st-century-truck-partnership>

⁷ <http://www.trb.org/TRBAVSMForum/AVSMForum.aspx>

⁸ <http://www.trb.org/TRBAVSMForum/AVSMForum.aspx>

Research Highlights

FY2018 was the second year of the Energy Efficient Mobility Systems Program, and many of 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 in FY2018, and is focused on delivering large-scale results during FY2019. Several new projects were initiated within the High Performance Computing and Big Data research area during FY2018, while the projects within EEMS' Advanced R&D portfolio made significant progress. Meanwhile, advancements were made in the modeling, simulation, evaluation, and data management tools that support the EEMS Program and VTO more broadly. Results, insights, and progress from these four areas 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, LBNL and INL performed modeling that indicates that longer driving range (larger batteries) leads to a smaller commercial AEV fleet size, higher investment costs for the AEVs, less daytime charging demand, and lower investment costs for charging systems. The modeling results find that in terms of fleet operating costs (fuel plus the cost of PEV chargers), these costs are typically lower than the operating costs of a comparable gasoline ICE fleet across a wide range of the number of PEV charging points in the network. *(AFI Pillar Task 2.3, Fuel Selection for Fully Automated Commercially Owned Taxi Fleet)*

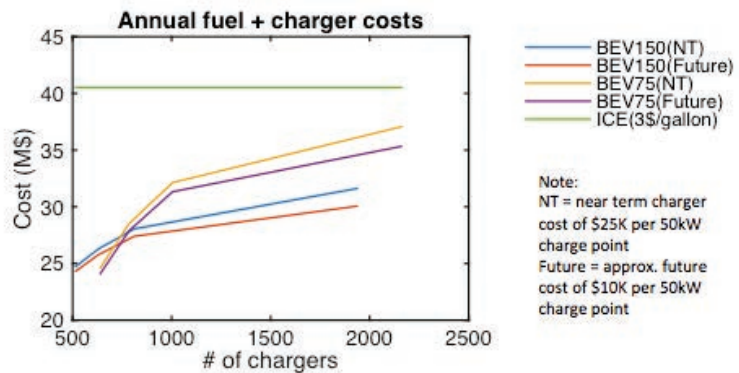
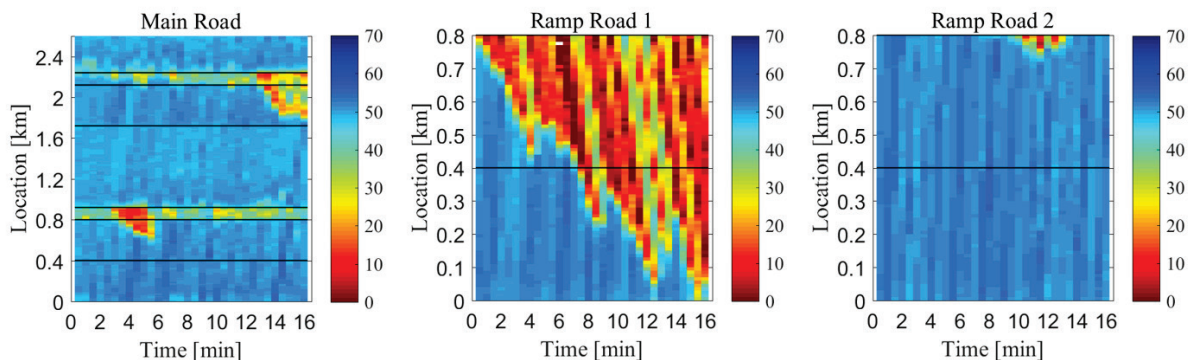
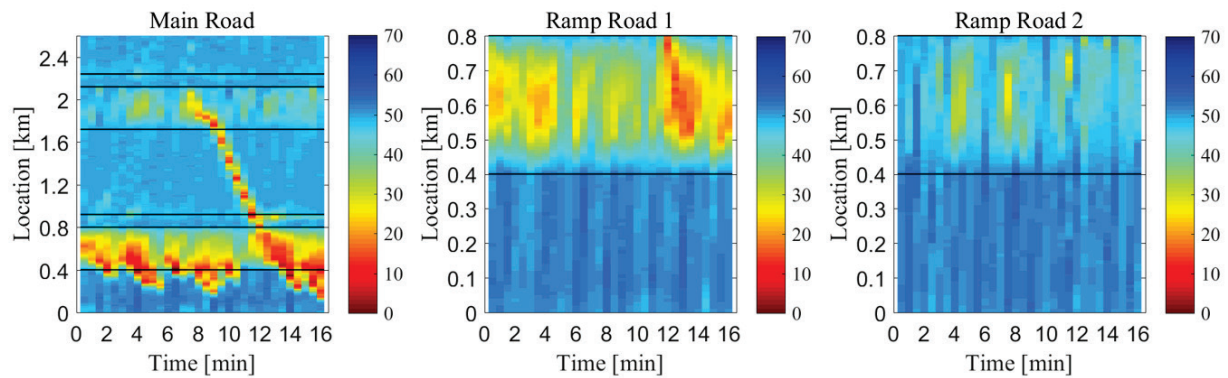


Figure-1 Total Operational Cost Comparison between ICEV and EV fleets

- A CAVS Pillar task performed by ORNL developed and tested an optimal traffic coordination controller on a hypothetical highway corridor with two on-ramps. In a scenario with partial penetration of CAVs, preliminary results reveal that 60% penetration of CAVs can aid to mitigate the propagation of traffic bottlenecks at the expense of a slight speed reduction on the main road for the hypothetical highway corridor under assessment. *(CAVS Pillar Task 2.1, Multi-Scale, multi-scenario assessment of system optimization opportunities due to vehicle connectivity and automation)*



(a) Scenario 1: 0% Penetration Heavy-Duty CAVs, 0% Penetration Light-Duty CAVs



(b) Scenario 2: 100% Penetration Heavy-Duty CAVs, 60% Penetration Light-Duty CAVs

Figure-2 Spatial-temporal distribution of mean speed plots of main and ramp roads (Black lines indicate the start and end of the control and/or merging zones)

- A CAVS Pillar task performed by ANL compared several proposed eco-approach strategies for vehicles with different power trains on a dynamometer. The analysis compared the proposed eco-approach strategies to a standard intersection approach strategy. The eco-approach strategies assume more information regarding the traffic light state and allow for a smoother, more managed stop than a standard intersection strategy. Electrified vehicles show higher relative fuel/energy consumption benefits than conventional vehicles when using the eco-approach strategies. The HEV and BEV enjoy fuel and energy consumption benefits of 12-20% thanks to the eco-approach strategies, with the higher benefits realized by the HEV. The conventional vehicles, on the other hand, see fuel consumption benefits of 7-12%, with the higher benefits attained by the vehicle without idle stop-start technology. (CAV Pillar Task 7A.3.4 Focused Validation of Select SMART Simulation Activities)

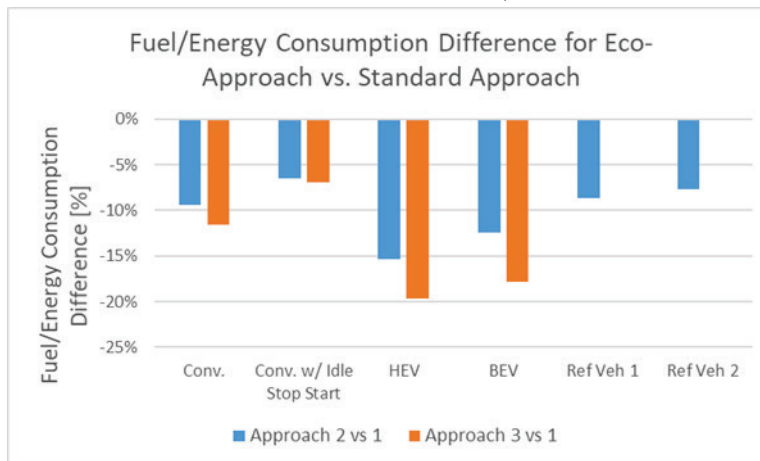


Figure-3 Focused Validation of Select SMART Simulation Activities -Summary of the relative fuel and energy consumption of approach strategies 2 and 3 compared to approach 1 for Situation 2

- The CAVS Pillar work by LBNL developed a cooperative traffic signal control algorithm that aims to maximize the intersection throughput by using the capabilities of the CACC vehicle strings. The proposed algorithm outperforms the traditional actuated signal controllers because it recognizes that vehicles in CACC strings can utilize the green time resource more efficiently than the manually driven vehicles, and thus would assign longer green time to an approach that accommodates more CACC vehicle strings than other approaches (CAV Pillar Task 7A.1.2, Traffic Microsimulation of Energy Impacts of CAV Concepts at Various Market Penetrations)

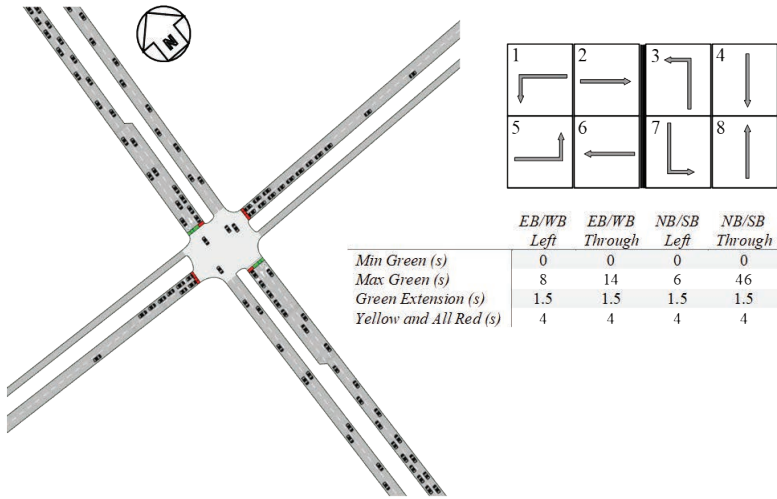


Figure-4 - Simulated intersection and actuated control parameters

- Depending on vehicle and automated vehicle (AV) technology characteristics, as well as behavioral assumptions, CAV pillar researchers from ANL estimated fuel consumption reduction by 2040 as high as 74%, even under up to 64% increase in VMT, when vehicle electrification and efficiency gains are combined with pricing strategies to limit unloaded miles. However, energy consumption reduction could be as low as 6% when considering low vehicle electrification and other advanced technology penetration, while VMT could increase up to 85% when considering high AV penetration and lack of an unloaded mileage pricing strategy. (CAV Pillar Task 1.3, Impact of CAVs on Energy, GHG, and Mobility in a Metropolitan Area)

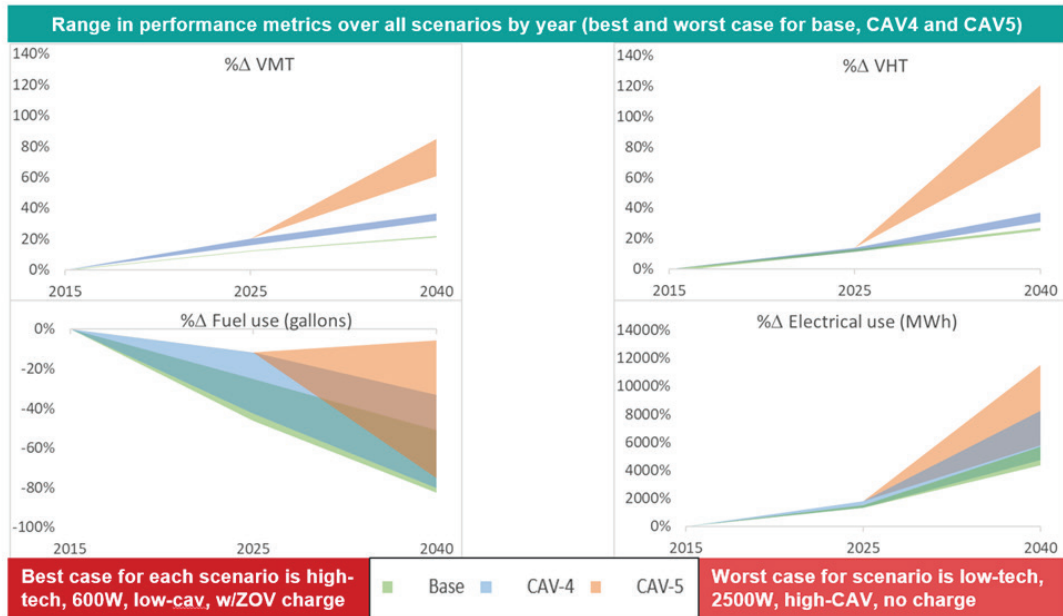


Figure-5 - Best and worst case performance metrics over time under privately owned, Level 4/5 CAV scenarios

- Within the Mobility Decision Science pillar, LBNL investigated the medium-term impact of behavioral sensitivity to mode through sensitivity analysis of San Francisco area travelers. Using a calibrated model with heterogeneous values of time, they assessed the sensitivity of the travelers to changes in cost of each mode. Changes to the cost of gasoline (+/- 50%), the cost of ride hailing (+/-25%), and the cost of transit (+/-50%) can yield substantial shifts in modal share and substantial changes in system energy consumption, as much as 18%.*(MDS Task 3.1: Mobility Behavior and System Energy Efficiency: Plug-in Electric Vehicle Benefits Analysis)*

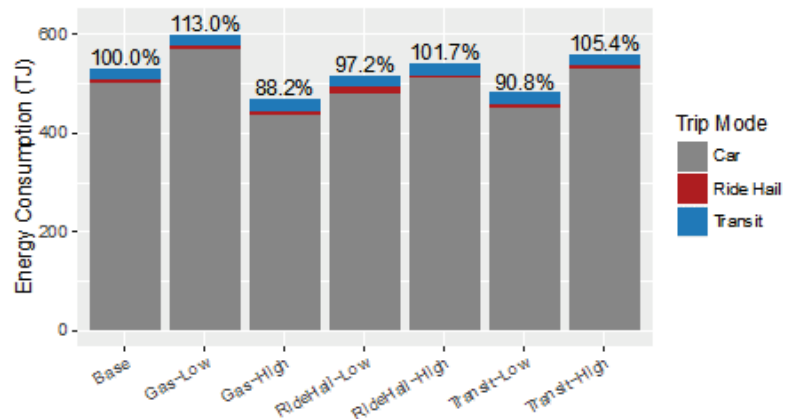


Figure-6 - Modal shares for the Base San Francisco Bay Area scenario and three sets of variations with cost of modes shifted +/-50% (for gasoline and transit) or +/-25% (for ride hail).

- Under the Multi-Modal Transportation pillar, ORNL, NREL, and INL coordinated with UPS to evaluate innovative opportunities to improve the cost and efficiency of last-mile freight delivery. The analysis concluded that that fully-electric delivery trucks will significantly reduce energy consumption. The use of parcel lockers for package delivery may also reduce energy usage in suburban locations where there are fewer through-streets and more cul-de-sacs due to their ability to significantly reduce miles traveled for delivery. *(MM Pillar Task 3.1, Optimization of Intra-City Freight Movement with New Delivery Methods)*

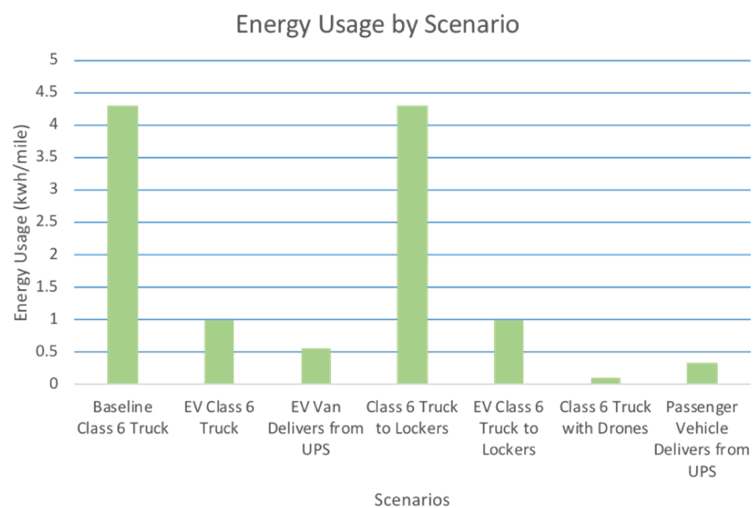


Figure-7 – Energy consumption rate for baseline and alternative freight delivery scenarios

- The Multi-Modal Transportation pillar team of ANL, NREL, and INL 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. National impact analysis found that electrified Class 7&8 electric truck with 500-mi electric range could potentially reduce the petroleum consumption by 1.61 quads in 2050, while the electricity consumption increases by 0.99 quad, compared to EIA’s AEO2017 reference case. (MM Pillar Task 2.1, Energy Analysis and Optimization of Multi-Modal Inter-City Freight Movement)

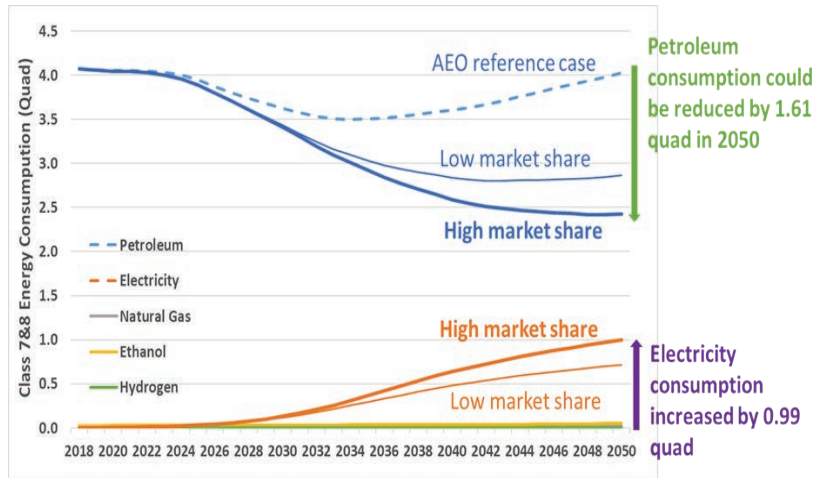


Figure-8 - Energy Impact of Electrified Class 7&8 Electric Truck in the United States (500-mi electric range)

- The Urban Science pillar, through efforts led by NREL, has developed, tested, and refined a comprehensive metric that reflects energy consumption, affordability and accessibility of current and future mobility services - to quantify the quality of mobility. The refined Mobility Energy Productivity metric (MEP 2.0) is being utilized to quantify the impact of various potential future scenarios that are then simulated in the integration of a number of different transportation models carried out as a part of the DOE SMART Mobility Consortium research (US Pillar Task 2.1.2 Mobility Energy Productivity Metric)

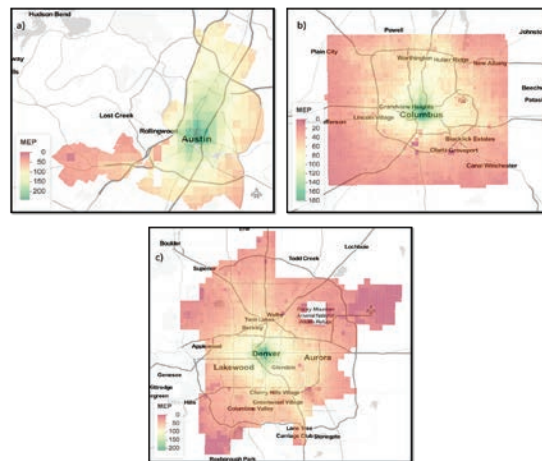


Figure-9 - MEP 2.0 methodology applied to: a) Austin, TX; b) Columbus, OH; c) Denver, CO

- The High Performance Computing and Big Data work by ORNL developed algorithms that teach GRIDSMA^{RT} cameras to estimate fuel consumption of vehicles in their visual field and use this capability to improve energy efficiency by changing timing and phasing of traffic lights, while minimizing penalties to throughput and mobility. ORNL developed and deployed computer vision algorithms to segment vehicles from the background, thus capturing a view of the identified vehicle type from multiple ranges from the camera. (HPC & BD Pillar Task - Reinforcement Learning-based Traffic Control to Optimize Energy Usage and Throughput)



Figure-10 - GRIDSMA^{RT} capture labeled the ground imager data as a “Ford Transit Connect,” which has an estimated fuel efficiency of 28 MPG.

- The Big Data Solutions for Mobility project by LBNL, PNNL, and ANL is applying high performance computing to address challenges in large transportation systems that were otherwise not possible. In particular, the team developed a proof-of-concept, scalable transportation system simulator that implements parallel discrete event simulation on high-performance computers. Using real data, the system is able to represent millions of nodes, links, and agents to simulate the movement of the population through the San Francisco Bay Area road network and provide estimates of the associated congestion, energy usage, and productivity loss. Preliminary results show excellent scalability on multiple compute nodes for statically-routed agents, simulating 9.5 million trip legs over a road network with 1.1 million nodes and 2.2 million links, processing 2.4 billion events in less than 30 seconds. The capability to run simulations that process billions of events within minutes or seconds will enable mobility researchers, industry, and transportation entities to better understand and predict future behavior, and potentially even be able to dynamically re-route travelers to reduce congestion, reduce travel time, and energy consumed.

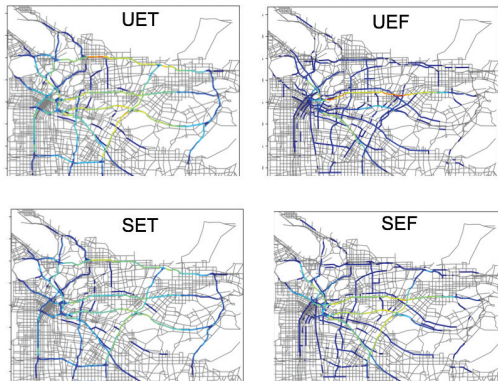


Figure-11 – Flow Impact due to Different Optimization Solutions: Time-Based User Equilibrium (UET); Time-Based System Optimal (SET); Fuel-Based User Equilibrium (UEF); Fuel-Based System Optimal (SEF)

- The Core Modeling and Simulation work by ANL demonstrated the accuracy of Autonomie energy consumption prediction for more than 200 specific vehicle models (143 conventional vehicles, 52 HEVs, 13 PHEVs and 2 EVs) using on-road data collected by the University of Michigan. A pre-release version of a new workflow manager (AMBER) was successfully developed and tested by several OEMs. The tool will enable VTO and the research community to develop and manage complex workflows across multiple tools including for Smart Mobility. (Core MSE Task - Maintenance; Tools; Real World Energy Impact Estimation; and Toyota Prius Prime Validation (ANL)).

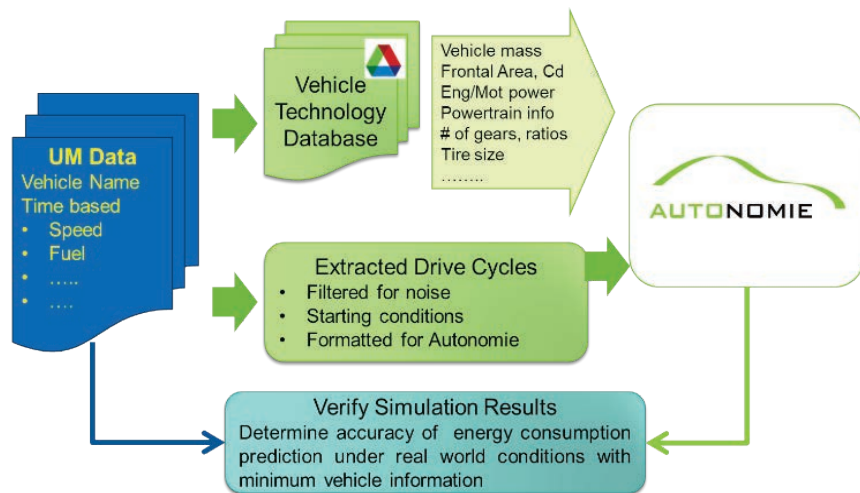
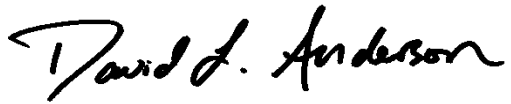


Figure-12 – Real-world Energy Impact Estimation Approach Overview

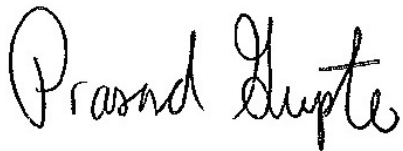
We are pleased to submit the Annual Progress Report for the Energy Efficient Mobility Systems Program for FY 2018. Inquiries regarding the EEMS Program and its research activities may be directed to the undersigned.



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Program Manager



Erin E. Boyd
Technology Manager



Prasad Gupte
Technology Manager

I SMART Mobility- Advanced Fueling Infrastructure (AFI)

I.1 National Energy Impact of Electrified Ride-hailing Vehicles with Varying Infrastructure Support (ANL, NREL, ORNL)

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Start Date: October 1, 2017	End Date: September 30, 2018
Project Funding (FY18): \$235,000	DOE share: \$235,000 Non-DOE share: \$0

Project Introduction

Infrastructure has long been a major barrier to battery electric vehicles (BEVs) adoption [1]. Cost-effective charging infrastructure is crucial to support the future energy efficient transportation systems. The rapid development and deployment of advanced public charging technologies (e.g., direct current fast charging (DCFC)), coupled with other smart mobility solutions such as vehicle connectivity and shared mobility, will affect future vehicle ownership and use, electricity generation, and alternative fuel energy market. This will further result 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 BEVs.

Objectives

Within this scope, our objective is to quantify the national energy impact of ride-hailing PEVs as compared with privately owned PEVs and ride-hailing ICEVs with varying infrastructure support (e.g. Level 2, DCFC,

high power FC). This task helps DOE to understand changes in petroleum and electricity consumption while providing mobility of service (e.g. ride-hailing) using infrastructure supported electrification. This task quantifies the petroleum reduction potential of using charging infrastructure to support electrified ride-hailing.

Approach

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 [2]. 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 [3]. MA3T is a Market Acceptance of Advanced Automotive Technologies model developed by the Oak Ridge National Laboratory [4].

Market Share and Stock

Expand on AFI Task 2 regional charging infrastructure deployment findings in Columbus, Ohio and Austin, Texas, this task first analyzed the impact of public charging infrastructure on the BEV adoption, both ride-hailing vehicle and private-used vehicles, show in Figure I.1.1. The major outputs from AFI Task 2 that would affect the BEV adoption include charging coverage and charging power.

Then, we estimated the number of ride-hailing and private vehicles on the road at given year using projected market shares, % of shared vehicles and vehicle survival pattern. Theoretically, with known historical vehicle sales and survival function of vehicle type i, the vehicle stock in year m (Stock i, m) can be determined as

$$Stock_{i,m} = \sum_{j=0}^{\sigma} [Sale_{i,m-j} \cdot r(j)_i]$$

where j and σ represent the vehicle age and the potential longest vehicle service years, respectively; Sale i,m-j represents the new vehicle sales of type i vehicles in model year m-j; and r(j) i is the survival function. Vehicle type i here refers to BEVs and replaced conventional vehicles.

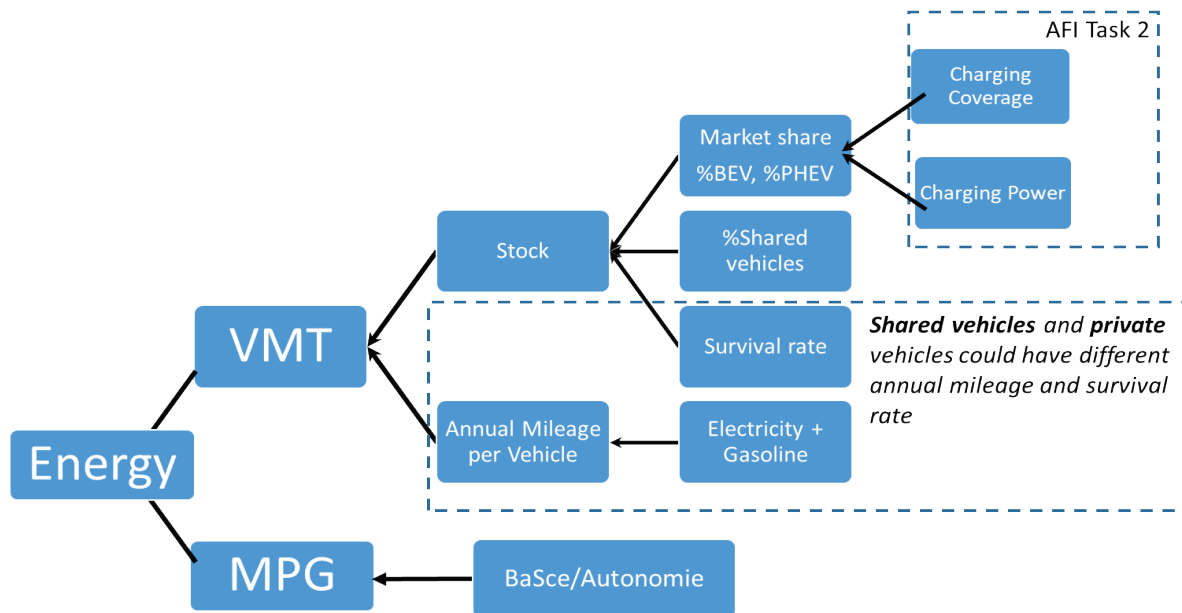


Figure I.1.1 Approach for quantifying the national energy impact of ride-hailing PEVs

Percent Shared Vehicles

Although there are several types of shared mobility in the market, this study only considers ride-hailing vehicles as the type of shared vehicles to align with the scope of AFI task 2. For Columbus, Ohio, AFI Task 2 emulated a high ride-hailing demand scenario. Over 95% trips could be served by ride-hailing vehicles in this scenario. For Austin, TX, because the data AFI Task 2 used is from RideAustin, in which all vehicles are also ride-hailing vehicles. Therefore we assumed 100% ride-hailing vehicles in this study. However, because ride-hailing vehicles have different usage pattern and survival function, it would affect the energy impact in the end if different percentages of shared vehicles are assumed. Currently there are very limited literature making projections of market share of ride-hailing vehicles in the future.

Survival Rate and Annual Mileage

Ride-hailing vehicles and private vehicles have very different usage pattern (e.g. daily mileage and annual mileage) and thus different survival pattern (e.g. lifetime). In average, the lifetime of private light duty vehicle (LDV) is about 14 years with about 170,000 lifetime vehicle miles traveled (VMT). Recent data from Populus shows that a full-time ride-hailing driver in average could drive about 27,000 miles/yr [5]. Assuming similar lifetime miles of private vehicles, the average life time of ride-hailing vehicles would be around 7 years which means ride-hailing vehicle would be scrapped faster than private vehicles.

Increased infrastructure deployment would also increase the mileage on electricity for Plug-in electric vehicles (PHEV). Percentage of miles on electricity, eVMT%, also comes from AFI Task 2 regional modeling results. For example, Columbus simulation results show that with increased infrastructure support, eVMT% of PHEV20 could increase from 23% to 64%.

Charging Availability

Alternative fuel data center (AFDC) provides the locations of existing charging stations and their charging level [6]. EVI-Pro estimates number of chargers by charging level needed for a given region based on given travel demand and PEV stock. Such output is converted to charging availability, which represents the percentage of the area that has charging stations. We estimated this ratio by dividing an urban area into small square grid cells, about 1*1 mile in this case. A cell is covered if charging stations are present inside the cell; otherwise the cell is not covered, shown in lower left of Figure I.1.2 (Wailuku HI). For example, California has the largest urban area in the U.S., about 16,724 total cells. The state also has a wide coverage with urban public charging stations, about 12,355 stations covering 1,739 cells (5). Therefore, the charging availability in California urban area is about 10.3% (i.e., $1,739/16,724=10.3\%$) in 2017.

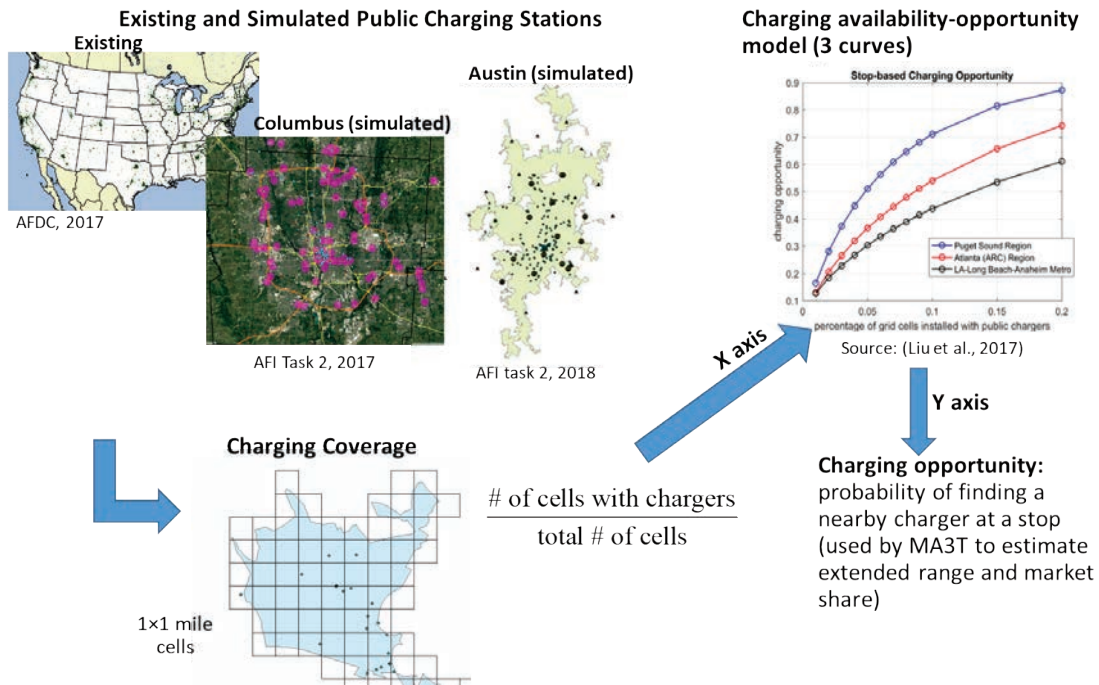


Figure I.1.2 Converting Charging Coverage from Regional Simulation Results to Charging Opportunity

The analysis horizon of this study is from 2017 to 2030, capturing the near-term impact. This study focus only on the urban areas with population over 50,000 according to U.S. Census (xXX). We have tried three different infrastructure scenarios through working with AFI Task 2 team. “Existing” means that infrastructure availability remain the same as 2017 level until 2030. “50 kW” stands for the scenario that most of public chargers remain low level DCFC, and the national average charging power is about 55.9 kW. “150 kW” stands for the scenario that all public charger will be DCFC with 150 kW charging power, shown in Table I.1.1. Higher charging power reduces the charging time which ultimately promotes the market adoption of BEVs. Also shown in Table I.1.1, the charging availability in 2017 are summarized from AFDC, while 2030 level are simulated results from AFI Task 2. The results reported in this report are based on regional simulation from Columbus, Ohio.

Table I.1.1 Existing (2017) and Simulated (2030) Charging Power and Charging Availability

Scenarios	2017		2030	
	Charging Availability	Ave. Power (KW)	Charging Availability	Ave. Power (KW)
Existing	5.3%	11.4	5.3%	11.4
50kW			15.2%	55.9
150kW			15.2%	150

Charging Opportunity:

We then translated charging availability to charging opportunity in each state, urban areas only. Charging opportunity is defined as the probability of finding a nearby charger at a stop. Such probability is developed using the GPS survey data in Seattle, Los Angeles, and Atlanta, and considered the geographical overlap between the charging network and travel activities. The charging opportunity and power are inputs to the MA3T model to evaluate impacts of public charging infrastructure on the PEV adoption by state. We conducted several iterations between EVI-Pro and

MA3T. EVI-Pro starts with certain assumption of PEV adoption to give charging availability. Such charging availability might stimulate more PEV adoption. In the end, we reach a balance that both market penetration and charging availability would not further increased (i.e. $\Delta \%PEV < 1\%$). Although currently we only have charging opportunity curves for these three cities, we found out the opportunity is highly related to the average trip distance, daily distance, average dwelling time at public locations of that given region, etc. We are currently using NHTS 2017 to develop some understanding that for a given city, what possible charging opportunity it might have comparing to the other three cities with a given charging coverage [8]. In FY18, we also develop charging opportunity curves for Columbus and Austin using available travel data.

Results

Market Shares

Figure I.1.3 shows the projections of BEV market shares by year under three scenarios. In “Existing” scenario, BEV market share could reach 32.4% by 2030 mainly due to technology improvement and price drop. Increased charging infrastructure availability and charging power could further increase the BEV market penetrations to 41% (50 kW scenario) and 50% (150 kW scenario) in urban areas. Figure I.1.3 also indicates that investment in public charging infrastructure has continuous impacts on the BEV adoption. Though not shown in Figure I.1.3, the PHEV has much less sales and smaller population than BEV in 2030. The impacts of public charging infrastructure on PHEV market is not significant.

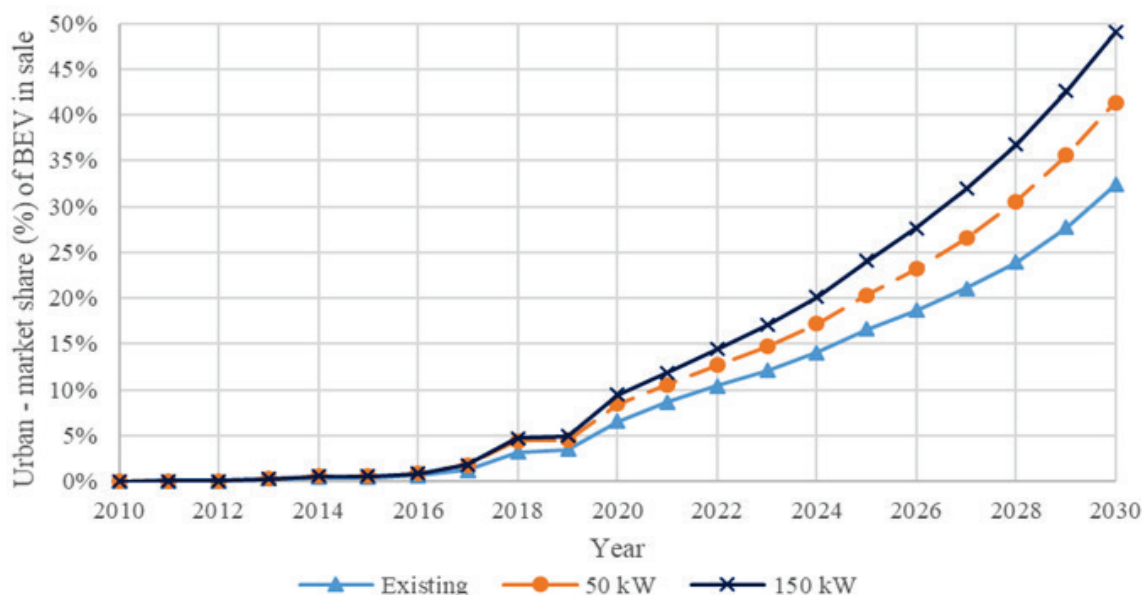


Figure I.1.3 BEV Market penetrations with different levels of infrastructure support

National Energy Impact of Ride-hailing Electrified Ride-hailing Vehicles

Based on BEV market shares by year, survival function and annual mileage per vintage, we first estimated total numbers of electrified ride-hailing vehicles on the road by year and their miles traveled. Then, with %eVMT and vehicle efficiency (MPGGE), we quantified the national petroleum and electricity consumption under different scenarios. In order to compare with privately owned PEVs and ride-hailing conventional vehicles, we separated the impact of faster vehicle turn-over rate due to ride-hailing and increased infrastructure support, shown in Figure I.1.4. In Figure I.1.4, “-Infrastructure” stands for “Existing” infrastructure availability, while “+Infrastructure” stands for future improved infrastructure availability and charging power. Figure I.1.4 shows the results for 150 kW scenario. “+Ride Hailing” means 100% vehicles are used as ride-hailing vehicles, which stands for an extremely high ride hailing demand. In next step, we will try

scenarios with different ride-hailing demand. “-Ride Hailing” means 100% vehicles are private used vehicles. Comparing to the left side of Figure I.1.4, right side shows the energy impact of improved infrastructure when controlling the impact due to ride-hailing. For example, compared to “-Infrastructure/-Ride Hailing” in 2017, improved infrastructure supporting private PEVs could reduce gasoline consumption from 15.44 quad to 9.77 quad in 2030, but could increase electricity consumption from almost 0 to 1.39 quad mainly due to significantly increased PEV market penetration, 50% by 2030. Moreover, compared to “-Infrastructure/-Ride Hailing” in 2017, “+Infrastructure/+Ride Hailing” could further reduced the gasoline consumption to 7.58 quad in 2030 mainly due to increased PEV market penetration, increased eVMT, and shorter vehicle lifetime. It’s interesting to note that shorter vehicle lifetime due to high annual mileage also reduce gasoline consumption because faster fleet turn-over rate brings newer and more efficient vehicles on the road. However, in this analysis we assumed no induced VMT demand and no changes in total number of vehicles adopted in the future due to convenience of ride-hailing. We used EIA’s 2017 projections of total light-duty vehicle sales reported in their annual energy outlook to estimate vehicle sales by year by 2030.

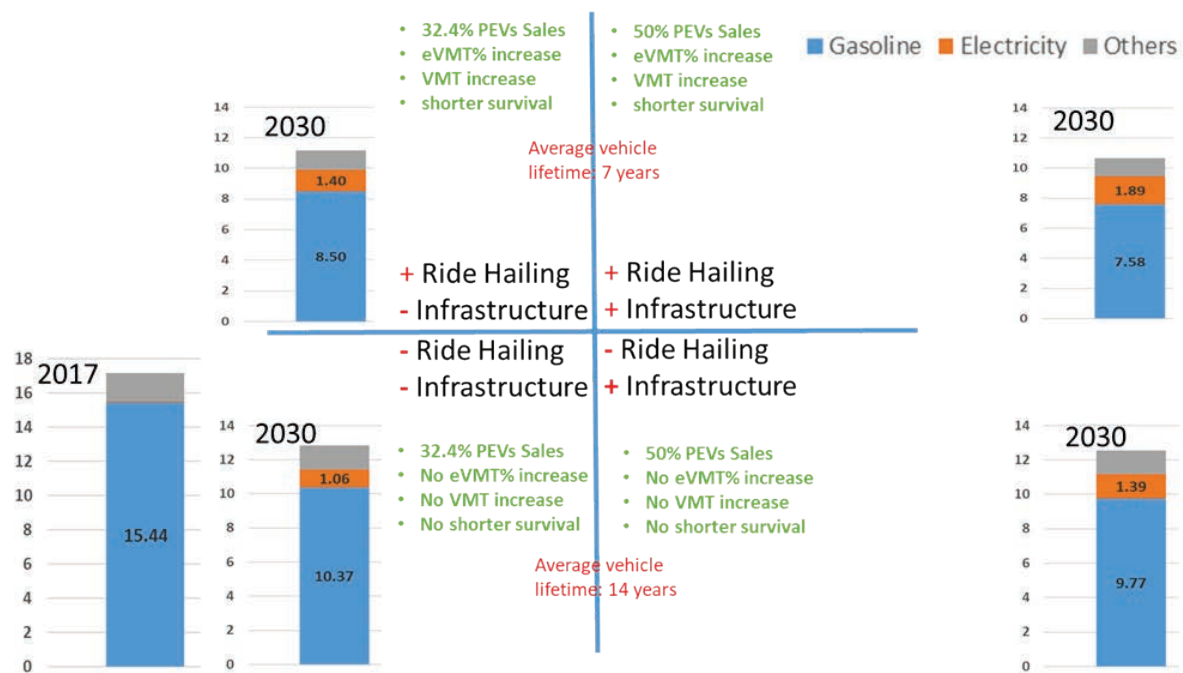


Figure I.1.4 National Energy Impact of Electrified Ride-hailing LDVs in 2030

Conclusions

National impact analysis found that using public charging infrastructure to support electrified ride-hailing vehicle could potentially reducing petroleum consumption by 7.68 quadrillion BTUs and 2.79 quadrillion BTUs compared to 2017 and 2030 level, respectively, due to induced PEV adoption, increased eVMT and faster vehicle turnover rate. Induced PEV adoption is attributed to significantly increased average charging power and charging availability.

Key Publications

1. F. Xie, Z. Lin, Y. Zhou, C. Rames, E. Wood and E. Konton, Will Advanced Public Charging Infrastructure Speed Up Electrification of Future Transportation? Proceedings of IEEE ITSC Annual Meeting, Maui, Hawaii, November 3-7, 2018.

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5. National Renewable Energy Laboratory, Preliminary findings from Populus TNC driver survey, Aug.2018.
6. Alternative Fuel Data Center, Electric Vehicle Charging Stations, https://www.afdc.energy.gov/fuels/electricity_stations.html
7. U.S. Census, 2010 Census Urban and Rural Classification and Urban Area Criteria, <https://www.census.gov/geo/reference/ua/urban-rural-2010.html>
8. U.S. DOT Federal Highway Administration, National Household Travel Survey 2017, <https://nhts.ornl.gov/>

Acknowledgements

This work is supported by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy (EERE), Vehicle Technologies Office (VTO). We thank David Anderson, program manager of Energy Efficient Mobility Systems, for his generous support. We also thank John Smart, the pillar lead of Advanced Fueling Infrastructure for his support and guidance on this task. We acknowledge Clement Rames and Eleftheria Kontou from NREL for their effort and time spent on this task.

I.2 Fuel Selection of Human-Driven Ride-Hailing Vehicles (INL) [Task 2.1]

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Start Date: October 1, 2016 End Date: September 30, 2019
Project Funding (FY18): \$1,070,000 DOE share: \$1,070,000 Non-DOE share: \$0

Project Introduction

Over the past several years, ride-hailing has emerged as a major form of transportation. Ride-hailing services are performed by drivers who own their vehicles and use them for personal and shared driving. These new services are causing the operating patterns of many personally owned vehicles used for personal and shared driving to be very different from those used only for personal use. Electric vehicles (EVs) have been widely reported as desirable ride-hailing vehicles due to low per-mile operating costs, but the overall cost to own and operate ride-hailing vehicles of different architectures is not well understood. The impacts that changing operating patterns and varying fuel types will have on drivers and infrastructure needed further analysis.

Objectives

Using gasoline and electricity as fuels for ride-hailing vehicles have different implications on energy consumption, infrastructure needs, and costs to drivers. The Advanced Fueling Infrastructure (AFI) Task 2.1 team used simulation to study estimated potential DC fast charging (DCFC) needs by EV ride-hailing services in Columbus, OH, and Austin, TX. This task then compared the relative advantages of EVs to other vehicle types for ride-hailing drivers in different scenarios.

Approach

In order to meet the objectives, this task sought to:

- Understand travel patterns and quantify operations of real-world ride-hailing vehicles from multiple sources, including data from INRIX personal travel data in Columbus, OH; RideAustin; ReachNow; Columbus Yellow Cab; Populus; and RIES.
- Determine infrastructure needs of ride-hailing vehicles by simulating real-world data in EVI-Pro.
- Evaluate economics of plug-in EVs and gasoline-fueled vehicles for several ride-hailing scenarios.

Due to the unavailability of ride-hailing vehicle data at the start of this task, a heuristic algorithm was developed to emulate TNC vehicle data from personal trip data collected by INRIX in Columbus, OH. This travel was simulated in EVI-Pro to determine TNC charging needs if the drivers were using EVs, and the costs were calculated to install and operate the simulated chargers. Costs varied widely among the 12 DC fast charging sites that were recommended by EVI-Pro simulations, with costs ranging from \$4 to \$40 per charging

session. Analysis of the station costs showed that while installation costs can be high and vary from site to site, the most important factor in achieving low costs is high station utilization.

As real-world TNC vehicle data became available to the group from RideAustin, EVI-Pro simulations were used to determine what the charging needs would be for actual ride-hailing drivers. Up until this point, it was assumed that ride-hailing drivers would want to use a battery EV (BEV), but there had been no basis for that assumption. To understand whether it would make sense for those drivers to use BEVs, the costs to own and operate different vehicle types were calculated using the RideAustin data and EVI-Pro simulations.

With this approach, this task has developed an understanding of real-world ride-hailing operation and evaluated the costs of charging infrastructure and vehicle use. This has provided insights into the suitability of EVs as ride-hailing vehicles and provided context necessary for accurate assessment.

Results

Real-world ride-hailing data from RideAustin, a non-profit ride-hailing company in Austin, TX, was analyzed to understand the typical travel patterns of ride-hailing drivers. The breakdown of driver segments is shown in Table I.2.1.

Table I.2.1 RideAustin driver segmentation statistics

	Part-time Driver	Half-time Driver	Full-time Driver
Hours per Week	<10	10-35	>35
Percent of Drivers	49%	40%	11%
Percent of Rides Provided	14%	57%	29%
Average Annualized Vehicles Miles Traveled	7,000	13,000	29,000

Nearly half of all drivers work less than 10 hours a week and drive 7,000 miles per year. Full-time drivers make up 11% of all drivers and average around 29,000 miles per year. Since full-time drivers would likely have the largest need for charging infrastructure, EVI-Pro analysis was focused on full-time drivers. Data from these drivers was simulated in EVI-Pro to determine the charging and infrastructure needs of ride-hailing drivers with EVs. Results of these simulations show that with 250 miles of driving range and home charging, EV drivers would need to charge during only 2% of their driving shifts, and only 10 DC fast chargers would be needed to support every 1,000 ride-hailing EVs. Without home charging, public infrastructure needs increase significantly. Since ride-hailing drivers use their own vehicles, they may only use a BEV if it costs less than other vehicle types. A total cost of ownership model was developed to assess the costs of owning and operating ride-hailing vehicles, including costs for vehicle depreciation, maintenance, fueling or charging, and fueling time during shifts, as downtime during shifts is a major opportunity cost for a driver. Applicable costs are aligned with those of other Department of Energy (DOE) studies. A comparison of costs was made for a full-time driver with access to home charging over a period of five years. The comparison showed that the total cost of a BEV250 would be slightly less than that of an internal combustion engine vehicle (ICEV) and more than a hybrid electric vehicle (HEV). These results can be affected significantly by the cost assumptions made and will not necessarily be the same for all driver use cases. The range of costs for different vehicle types is

shown in Figure I.2.1, where each bar shows how the cost can vary by changing one input value from the baseline cost to low and high cost scenarios that encompass a reasonable cost range for that input.

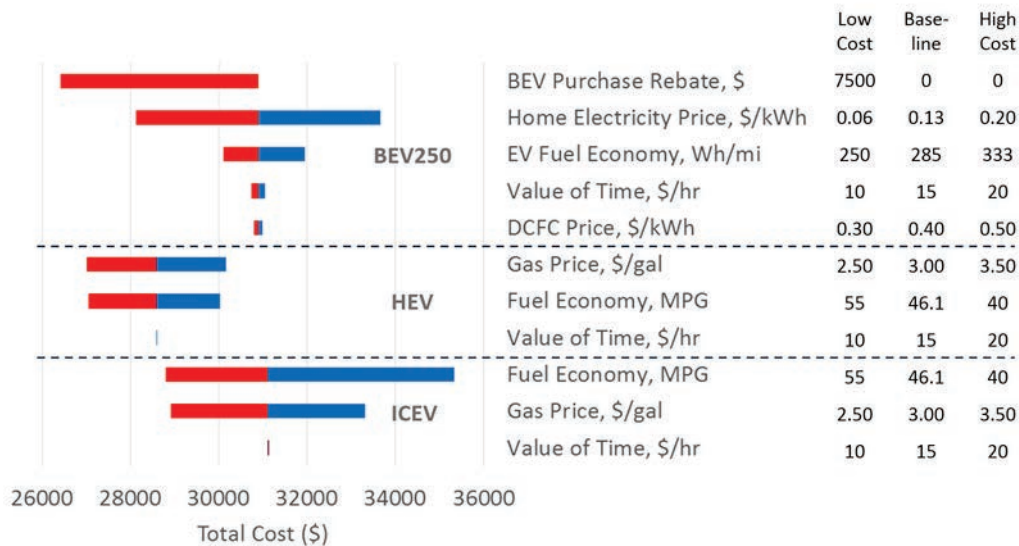


Figure I.2.1 Five-year cost of ownership for a full-time ride-hailing driver by cost component for each vehicle type, assuming driver has access to home charging

Different vehicle types can become significantly more, or less, desirable depending upon cost factors in a specific scenario. Geographic differences in electricity prices and changes in gas prices through time can have a major effect on the costs of owning a vehicle, as can personal preferences like driving style and vehicle size.

Conclusions

The results of this analysis show that, in many cases, BEVs can be the lowest cost vehicles for ride-hailing drivers, but not for every situation or every driver. The portion of drivers for which a BEV is the lowest cost may increase significantly if electricity costs are low in a certain area or if gas prices increase. In future analysis, these findings suggest that care needs to be taken when selecting the BEV mix for a given scenario. Analysis is often performed under the assumption that all vehicles will be BEVs, but that may only be valid for a certain portion of drivers to own BEVs. The effects that this might have on infrastructure requirements and usage is often overlooked and needs to be considered.

Interesting implications arise when these findings are combined with the previous conclusions of this task that DCFC costs are much less in highly utilized locations. DCFC deployment needs to be carefully balanced with the needs of BEV drivers such that there are enough opportunities for drivers to charge, but not so many chargers that low utilization drives high charging costs. This balance and its tradeoffs require further analysis.

Key Publications

1. Wood, E., Rames, C., Kontou, E., Motoaki, Y., Smart, J., and Zhou, Z., “Analysis of Fast Charging Station Network for Electrified Ride-Hailing Services,” SAE Technical Paper 2018-01-0667, 2018, doi:10.4271/2018-01-0667.

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1. Burnham, A., et al., “Enabling fast charging – Infrastructure and economic considerations.” *Journal of Power Sources*, Vol. 367, November 2017, pp. 237-249.

Acknowledgements

The authors would like to recognize the rest of the AFI Task 2.1 team including Eric Wood, Clement Rames, and Ria Kontou from National Renewable Energy Laboratory; Zhi Zhou from Argonne National Laboratory; and the leader of the AFI Pillar team, John Smart, from INL.

I.3 Fuel Selection in Automated Mobility Districts – Dynamic Wireless Power Transfer (DWPT) Feasibility Analysis (ORNL, NREL) [Task 2.2]

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End Date: September 30, 2018

Project Funding (FY18): \$235,000

DOE share: \$235,000

Non-DOE share: \$0

Project Introduction

Connected and automated systems are on path to dominate the future of vehicles, buildings, and the power grid due to the potential for significant improvements in energy efficiency, sustainability, security, congestion mitigation, and convenience. This transition will include the emergence of connected and automated vehicles (CAVs) for the transportation of people and goods.

Some of the areas are partially worked on in the field of CAVs, such as sensors, connectivity, and communications. However, refueling (charging) methods and the charging infrastructure requirements remain unaddressed. While having the self-driving and self-parking functionalities, not having self-charging capability would be a failure for the CAVs. Moreover, a fleet of a CAVs for ride-shared vehicle applications would be a high cost-intensive investment which requires very high-utilization; therefore, it would not be practical to stop and charge these vehicles in the middle of the day for several hours. With dynamic wireless charging systems, these vehicles can be recharged while they are in operation which eliminates the down time for these vehicles.

Not only for the CAVs but in general for all the EVs, range anxiety and the cost of battery packs are among the most important barriers against future adoption. As one means of increasing the adoption rate of E-CAVs (electrified connected and automated vehicles), wireless charging can gain considerable momentum due to ease of charging with no wired connection. Wireless charging is a safe, convenient, flexible, and efficient method for charging the electric vehicles [1]. Substantial reductions in petroleum consumption and greenhouse gas emissions are possible with electrified vehicles and roadways. In fact, WPT is a key enabling technology for the future of the CAVs but there is no specific research reported so far on WPT integrations of CAVs.

With dynamic wireless charging capability, CAVs can self-charge and also have ideally unlimited all-electric range and their battery packs can be reduced which would result in overall weight and cost reduction while improving the fuel economy. According to a study [2], the market share of plug-in EVs could increase up to 65% among the total light duty vehicle sales if 1% of the roadways were electrified with 60kW dynamic

wireless charging systems. As one means of increasing the adoption rate of EVs and electric CAVs, wireless charging has gained considerable momentum due to ease of charging with no wired connection. 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 size and 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. For the vehicle energy consumption levels, models and databases created by other national laboratories have been utilized. Team analyzed the point A-to-B constant speed modeling for light, medium, and heavy-duty vehicle classes considering the cases with and without auxiliary power. Constant speed modeling energy consumption models can be especially useful where the automated driving infrastructure can potentially eliminate the stops. Using the vehicle average power consumption levels and the route distance, the DWPT system can be sized in terms of the power level of the electrified roadway track and the section length of it under the assumption of rectangular and continuous power transfer profile to the vehicle.

In order to analyze the power transfer characteristics of long-track based DWPT deployments, team completed the finite element analysis (FEA) model of a DWPT road section. This FEA model validates and details all of the early assumptions in the power transfer continuity along the track. While the smaller coils approach has very high peak efficiency, since the coil length is limited, there are power pulsations as the vehicle passes over

one coil to another. Moreover, the energy delivered to the vehicle is limited in this approach since the energy delivery is a function of the time integration of the power transfer curve. With the long track approach, the power starts from zero and gradually increases to the peak value as the vehicle starts getting aligned with the transmit track; then, power transfer stays constant along the track, and it gradually falls as the vehicle clears the track. Since the track is relatively longer, the power transfer stays almost constant along the track. The FAE model developed in this quarter validates these power transfer characteristics while identifying the DWPT track parameters, track to vehicle power transfer efficiency as a function of the track length, and the mutual inductance variation with respect to the vehicle position. The DWPT track-to-vehicle mutual inductance has also been modeled which is an indication of the power transfer profile to the vehicle. The block diagram of the system analyzed is shown in Figure I.3.2.

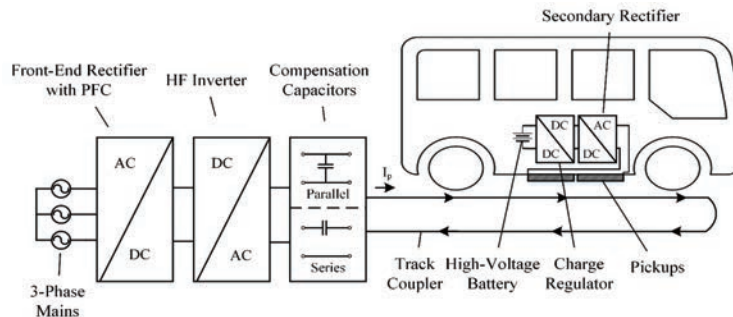


Figure I.3.1 Block diagram of a typical track-based DWPT system.

Once the power transfer characteristics are analyzed, team studied the optimal sizing of a dynamic wireless power transfer (DWPT) systems for highway applications. The system parameters must be selected carefully to reduce the overall cost per mile of DWPT. Among these parameters, system length is important due to its impact on the system coupling coefficient, overall efficiency, and the cost of construction and installation. The impact of this effect will increase if the quality factor of the system is low. Because high-efficiency operation is paramount for DWPT to be practical from both a capital and operational cost standpoint and the quality factors of systems may be limited, transmitter sizes will be constrained by the dimensions of smaller vehicles. In this case, it is advantageous to consider utilizing the longer lengths of heavier vehicles to have multiple paralleled receivers. This will both decrease the initial capital cost and ensure the maximum utilization of the DWPT system which will drive down the cost of using the system for all. If these costs are low enough, DWPT could revolutionize future transportation by eliminating range-anxiety and enabling long distance, charge-sustaining trips in CAVs.

DWPT would increase the mobility of both freight and passengers and ultimately help remove the barrier of long-distance travel from transportation electrification. The analysis included an interoperable DWPT system that can be used to charge all classes of CAVs including light-duty vehicles (LDV) and heavy-duty vehicles (HDV). For example, a DWPT system may be designed to have transmitter lengths shorter than the length of a HDV to maximize efficiency for an LDV. Due to this, it may rely on having multiple receivers on an HDV to scale the power transfer relative to an LDV. A block diagram of such a system with 100 kW transmitters is illustrated in Figure I.3.2. With 42% roadway coverage, the system could enable charge-sustaining operation for both LDVs and HDVs at 70 mph.

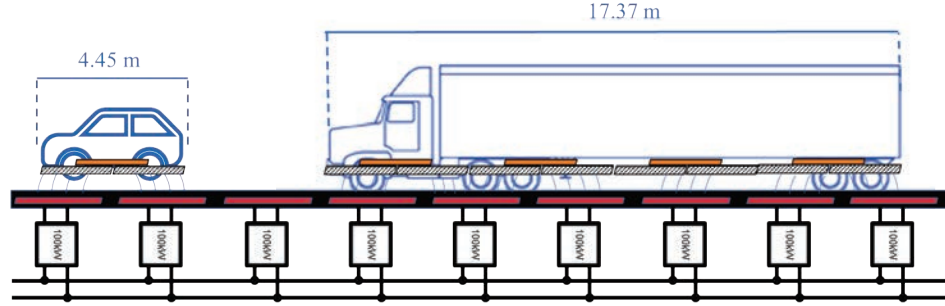


Figure I.3.2 An example of a DWPT system using paralleled short sectional 100 kW primary couplers and arrays of pickup couplers. As displayed, the light-duty vehicle is receiving 200 kW and the heavy-duty vehicle is receiving 600 kW.

For the system depicted in Figure I.3.2, a multi-objective optimization system based on the models is developed. The multi-objective optimization developed uses the following equations:

$$\min_{\mathbf{x}} f(\mathbf{x}, \mathbf{p}) = W_1 W_2 C_{inv}(\mathbf{x}, \mathbf{p}) + (1 - W_1) W_2 \cdot C_{road}(\mathbf{x}, \mathbf{p}) + (1 - W_2) C_{coupler}(\mathbf{x}, \mathbf{p}) \quad (1)$$

$$\bar{P} + P_{aux} - P_{sys} \cdot \frac{\ell_{vehicle}}{\ell_T} \cdot \beta_{road} \cdot \eta_{coupler}(\ell_T) \leq 0 \quad (2)$$

$$[0 \ 0.5 \ 0]^T \leq [P_{sys} \ \ell_T \ \beta_{road}]^T \leq [500 \text{ kW} \ 10 \text{ m} \ 1]^T$$

$$W_i \in (0, 1)$$

$$C_{inv}(\mathbf{x}, \mathbf{p}) = \frac{P_{sys} \beta_{road}}{\ell_T} \quad (3)$$

$$C_{road}(\mathbf{x}, \mathbf{p}) = \beta_{road} \quad (4)$$

$$C_{coupler}(\mathbf{x}, \mathbf{p}) = \frac{P_{sys} \beta_{road}}{\ell_T} \cdot (2\ell_T + 2W_T) \cdot N_T \quad (5)$$

The upper bound chosen for the system power rating P_{sys} is based on the limits of the current state-of-art high-power wireless power transfer systems. Three objective functions are used: $C_{inv}(x,p)$ represents the cost of power electronics, $C_{road}(x,p)$ is the cost of road construction, and $C_{coupler}(x,p)$ approximates the cost of the coupler material. The constraints of the optimization in equation (2) are charge-sustaining operation for the light and heavy-duty vehicles at a constant speed of 70 mph. $C_{inv}(x,p)$ is calculated by considering the number of power electronic converters needed when each inverter is connected to one transmitter. $C_{road}(x,p)$ is modeled as the road construction costs for trenching and resurfacing roadways to install the system. $C_{coupler}(x,p)$ is calculated as proportional to the amount of wire in air-core transmitters, given that the needed section of Litz wire is proportional to P_{sys} for a fixed output voltage. All these functions are scaled by appropriate economic values and then multiplied by varying weighting factors W_i to produce the objective function. This, with the inclusion of $\eta_{coupler}(\ell_T)$ in the constraints is used to generate the Pareto fronts of solutions by using a weighted sum method.

This project also evaluated the impact of the DWPT systems on the power system/grid in order to assess the grid infrastructure requirements that provides power to the DWPT systems. Team performed electromagnetic transient (EMT) studies to quantify the impact of DWPT systems on the grid. These studies are used to understand the grid infrastructure requirements to reduce the voltage variations in the grid. The reduced

voltage variations can improve the stability of grids and avoid inadvertent protection triggers. For the DWPT models, the DWPT system requirements were quantified based on the charge-sustaining mode of operation for the vehicles.

Results

The power consumption levels of an average passenger vehicle at different speeds are given in Figure I.3.3. According to this figure, for a vehicle travelling at 55 MPH, about 15kW dynamic wireless charging systems should be used continuously in order to achieve charge sustaining mode. Based on the energy consumption models, the DWPT kW-mile/100 miles coverage assessment for 100 miles for sustained constant speed are given in Figure I.3.4. 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.

For the FEA, team analyzed the embedded ferrite track efficiency and characteristics. When ferrites are embedded in the roadway, they reduce the efficiency of the track per unit length as their magnetic core losses are significant. This effect can be remedied by increasing the thickness of the ferrites (to reduce the peak flux density) but very thick ferrites may pose undue infrastructure costs. In this case, $P_{loss} = l_t(2N_{tp}I_p\rho J + p_f)$ where p_f is the ferrite loss per unit length. Figure I.3.5 shows the track-to-vehicle power transfer efficiency as a function of track length for various assumed ferrite thicknesses. With 1/16” thick embedded ferrites, the efficiency of a 100m track is about 84%. The efficiency increases to 92% and 95% for 2/16” and 3/16”, respectively. The dotted line depicts the loose upper bound on efficiency assuming lossless ferrites.

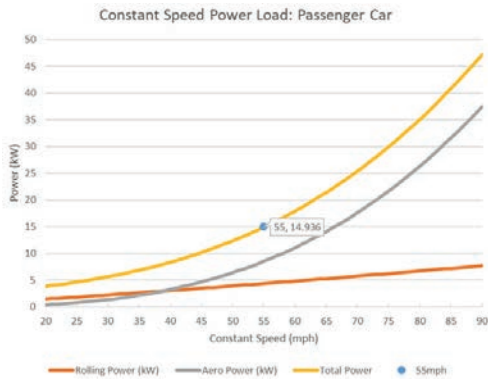


Figure I.3.3 Vehicle energy consumption levels at different constant travel speeds.

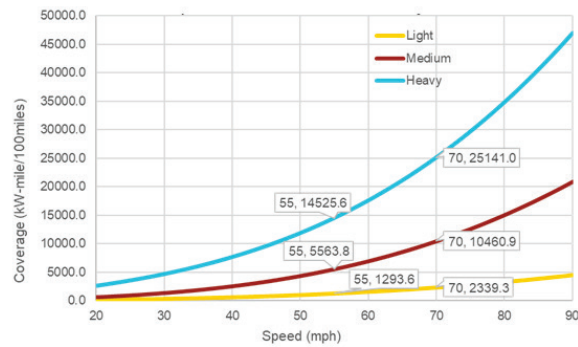


Figure I.3.4 DWPT coverage assessment for 100 miles of sustained constant speed traveling (drivetrain power only).

Table I.3.1 gives the parameters of a redesigned secondary coil assuming roadway embedded ferrites. With the use of ferrites, coupling factor between the track and the vehicle assembly increases which allows a smaller number of turns on the secondary to achieve the required mutual inductance. Figure I.3.6 shows the airgap field distribution which is much more directed than seen in ferrite-less configuration. The inductance per unit length and voltage per unit length of the track were 3.09uH/m and 0.380kV/m, respectively. For a 100m track, the total capacitor compensation voltage will need to be on the order of 38kV, which is about a 50% increase from the ferrite free track.

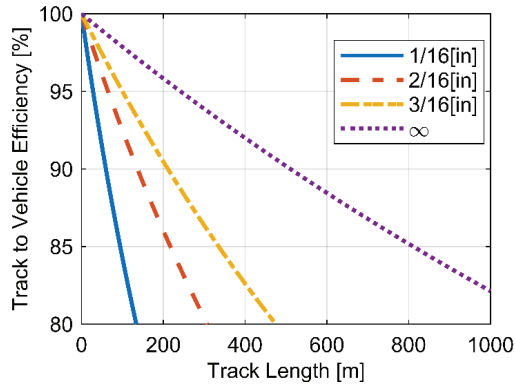


Figure I.3.5 Block diagram of a typical track-based DWPT system.

Table I.3.1 Example 100kW dynamic WPT secondary coil parameters for a roadway embedded ferrite track.

Parameter	Value
Ls	63.3 μ H
M	4.81 μ H
Vs	5.75 kV
Dx, Dy	48"
Ip	3.09 μ H/m
Vp	0.380 kV/m

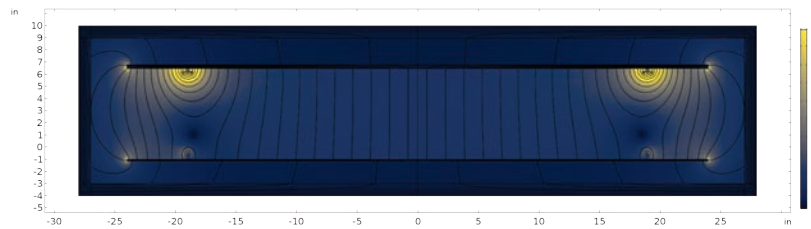


Figure I.3.6 Airgap field distribution for the 100kW DWPT system deployment.

Figure I.3.7 shows a normalized plot of track-to-vehicle coil mutual inductance as the vehicle moves over the track. Far away from the track, the mutual inductance is zero. As the vehicle begins to approach the track, the mutual inductance becomes negative (indicating reversed polarity coupling). Starting from a distance of about 1.5 coil diameters, the mutual inductance begins to ramp up. The peak value of about 1.1 times the nominal value is obtained when the vehicle coil is aligned with the end-turn of the track. The mutual inductance reaches the nominal steady-state value after the coil is overlapping the track by about 2 diameters. This mutual inductance variation demonstrates that the power transfer is continuous and has a trapezoidal profile as the vehicle moves over the track. As seen from the results in Figure I.3.8, it is important to limit the coverage of DWPT systems due to the large expense of roadway construction. However, there are practical tradeoffs between the power rating and coverage of the system. With low coverages, the onboard energy storage and electronics of EVs must facilitate high charge rates. However, the power ratings in this case may still be lower than what would be required with high-power static charging because the DWPT system can transfer energy over a longer period of time than static charging systems while the EV is on the move. There is also an upper limit to the area-related power density that can be achieved by wireless-charging systems.

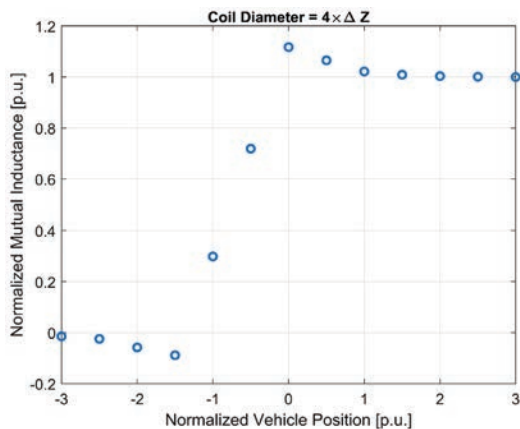


Figure I.3.7 Variation of track-to-vehicle mutual inductance with respect to vehicle position.

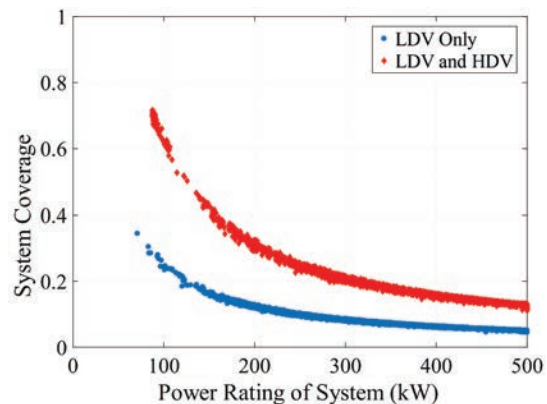


Figure I.3.8 Pareto solutions from the optimization model for two different cases (LDC only and LDC and HDV together)

Conclusions

This project analyzed the vehicle energy consumption levels and provided an optimization framework for the optimal size and design of the DWPT systems. The optimization framework was developed to analyze the relationship between the range extension through DWPT, power rating of the DWPT tracks, and the vehicle speeds. A finite element analysis model was created to analyze the power transfer characteristics, efficiency, and mutual inductance variations between the electrified roadway tracks and the vehicles. The optimization model has established the relationship between the system coverage and the system power rating both for light and heavy-duty vehicle classes. Finally, team also looked into the impact of the DWPT technology on the power grid in order to determine the grid infrastructure requirements supporting the DWPT technology deployment.

Key Publications

1. A. Foote and O. C. Onar, "A review of high-power wireless power transfer systems," in *Proc., IEEE Transportation Electrification Conference and Expo (ITEC)*, June 2017, Chicago, IL.
2. A. Foote, O. C. Onar, S. Debnath, M. Chinthavali, and B. Ozpineci, "Optimal Sizing of a Dynamic Wireless Power Transfer System for Highway Applications," in *Proc., IEEE Transportation Electrification Conference and Expo (ITEC)*, Long Beach, CA, June 2018.
3. S. Debnath, A. Foote, O. C. Onar, and Madhu Chinthavali, "Grid Impact Studies from Dynamic Wireless Charging in Smart Automated Highways," in *Proc., IEEE Transportation Electrification Conference and Expo (ITEC)*, Long Beach, CA, June 2018.

References

1. O. C. Onar, S. L. Campbell, M. Chinthavali, L. E. Seiber, and C. P. White, "A high-power wireless charging system and integration for a Toyota RAV4 electric vehicle," accepted for presentation, *IEEE Transportation Electrification Conference and Expo (ITEC)*, June 2016, Dearborn, MI.
2. Z. Li, J. Li, and J. Dong, "Dynamic wireless power transfer: Potential impact on plug-in electric vehicle adoption," *Society of Automotive Engineers Technical Paper*, 2014-01-1965.

I.4 Fuel Selection for Fully Automated Commercially Owned Taxi Fleet (LBNL/INL) [Task 2.3]

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Start Date: October 1, 2017

End Date: September 30, 2018

Project Funding (FY18): \$435,000

DOE share: \$435,000

Non-DOE share: \$0

Project Introduction

With recent advances in vehicle technology and expected future developments on transportation electrification and autonomous driving, it is now possible for ride-sharing or “transportation network companies” (TNCs), e.g., Uber and Lyft, to operate a fleet of autonomous plug-in electric vehicles (PEVs). On one hand, compared with traditional internal combustion vehicles (ICVs), PEVs generally have much higher fuel efficiency, thus will significantly reduce a company’s fuel costs. However, the company may also need to investment in sufficient charging infrastructure to eliminate the so-called “range anxiety” concerns for PEVs [1]. On the other hand, vehicle automation allows companies to hire less human drivers to save labor costs. However, autonomous vehicles could be every expensive especially in the early stage of commercialization. The above-mentioned factors will jointly alter the key economic considerations of a future ride-sharing or TNC Given a transportation network and historical data of trip demands, a TNC operator could then seek to find the optimal sizing (number of chargers) and placement (location) of PEV charging stations, as well as the PEV fleet size by minimizing the total cost.

Objectives

The objectives of this task are to: 1) further develop and implement a PEV charging system planning algorithm for support of automated PEV taxi systems; 2) use a nodal-based concept for identifying the locations of DC fast charging (DCFC) stations and defining the number of charge points at each station in a representative geographic area of the San Francisco (SF) Bay Area; 3) operating the BEAM model with the FCSPlan algorithm outputs for specific cases; 4) conducting model runs that vary the driving range of the vehicles (e.g., 75 and 150 miles driving range) and the power level of the DCFC network (50-500 kW per charge point); and 5) analyzing and summarizing task findings. The study applies previously developed automated plug-in electric vehicle (PEV) charging system design and fleet modeling algorithms to a real-world urban setting in the SF Bay Area, using the Behavior, Energy, Autonomy, and Mobility (BEAM) framework. It also considers PEV routing and rebalancing across the transportation network. We develop a column generation algorithm to approximately and efficiently solve the constructed problem. Based on the proposed framework, we calculate

the economics of electrifying a fully automated commercial ridesharing fleet and investigate various PEV and charging system parameters, e.g., PEV battery capacity and charging power of chargers, on the ridesharing systems' overall costs.

Approach

First, we have further developed and applied a joint fleet size and PEV charging station planning model (developed in AFI Task 4 FY17) called FCSPan to provide a charging system plan for use in BEAM framework simulations for the SF Bay Area. The model adopts Beam simulation to identify nodal charging demands of an automated electric vehicle (AEV) fleet [2], and utilizes the K-means algorithm to determine the locations of charging stations [3]. Then, a service level model is design to size each charging station subject to given quality of service constraints [4]. We have further expanded the proposed model to consider heterogeneous PEV driving range (battery capacities) and charger power. Our work now encompasses PEVs with different size batteries (driving range per charge) and charging networks with higher and lower power levels (charge rate per time). Finally, we have now integrated the use of the planning model with the BEAM framework to conduct analysis in a realistic metro region. This then provides insights on infrastructure planning for autonomous shared-use PEVs for policy makers, researchers and practitioners. Figure I.4.1 below shows the overall approach to the project.

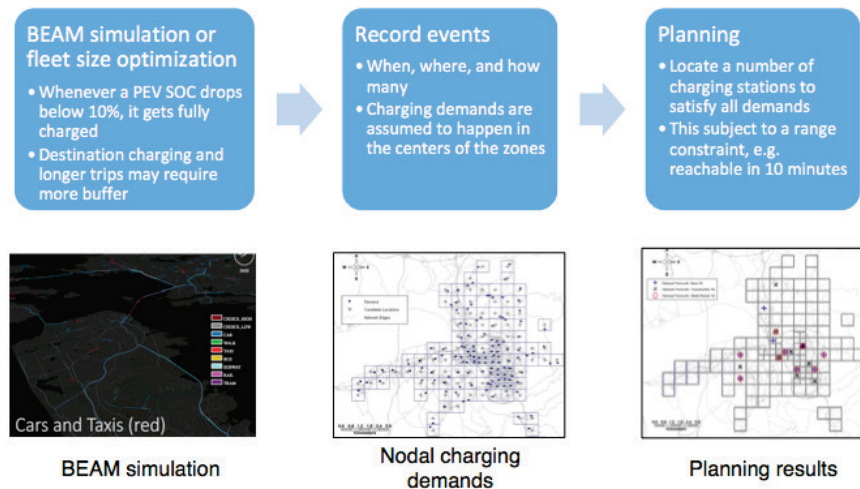


Figure I.4.1 Charging Station Planning Based on Nodal Demands

Results

We evaluated the charging stations requirement for different cases with different fleet size (5K, 10K, and 15K vehicles in fleet), different vehicle driving ranges (75 miles and 150 miles), and different rated charging power (50 kW and 250 kW). We calculated the level of charging demands, the number of required chargers, and the number of charging station locations for all the above cases. The results are illustrated in Figure I.4.2 through Figure I.4.5.

The number of charging demands is generally inversely proportional to fleet size. With more PEVs on road, a PEV will only be required to satisfy fewer ride-hailing requests. As a result, the average vehicle mileage will decrease, so that fewer PEVs may need to get charged. Number of charging demands is quite sensitive to PEV driving range. The daily charging demands decrease significantly when PEVs' driving range increase from 75 miles to 150 miles. Besides, the rated charging power can also impact number of charging demands. With higher charger power, PEVs will have less “down time” for charging and then more time for driving. Hence, higher charger power tends to encourage PEVs to charge more

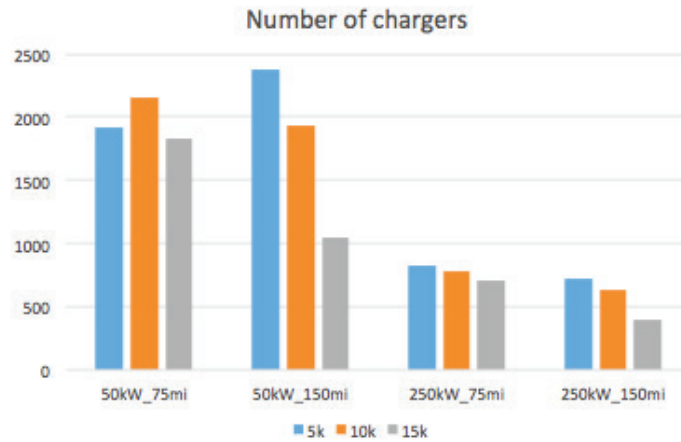


Figure I.4.2 Number of charging demands in different cases

The required number of chargers in Figure I.4.3 in the studied AF Bay Area is proportional to the number of charging demands as shown in Figure I.4.2, an intuitive result. Along with the number of charging demands, the number of chargers is also quite sensitive to charger power. A charger with a 250 kW capacity can satisfy more PEV charging demands than one with a 50 kW capacity, with a correspondingly higher turnover rate.

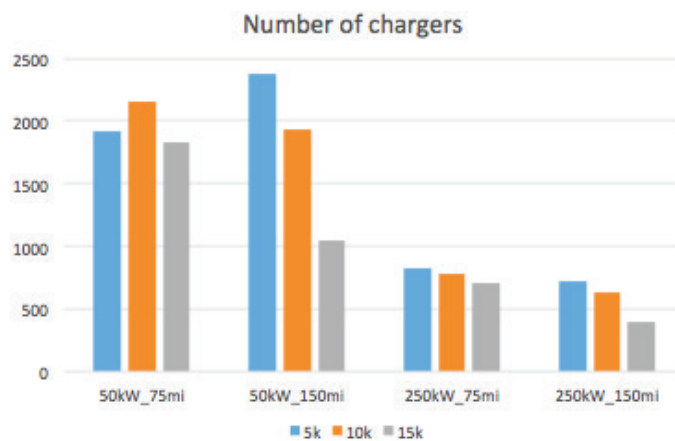


Figure I.4.3 Number of chargers in different cases

Along with the number of chargers, the number of charging stations is also an important metric to evaluate charging infrastructure demands. There is a trade-off between building large centralized charging stations with building smaller and more distributed charging stations, with fewer charging points per station. The former enhances the utilization level of the chargers but also increases PEV “down time” for accessing chargers. On the other hand, the latter are more convenient, being closer to the PEV demands, but may have a lower utilization level and requirement for more overall chargers. In our simulations, we assume that we need to locate enough charging stations so that 95% of demands can reach a charging station within 5 miles and the average driving distance between a demand to its nearest charger is 1 mile.

As shown in Figure I.4.4, the number of charging stations in different cases are all around 130, which is not significantly affected by fleet size, driving range, and charger power. This is because, in order to guarantee the charger accessibility described above, we need to make sure that we will install enough charging stations that cover the studied areas properly. We note here that the number of charging station locations is mainly determined by the coverage area. The location of charging demands and charging station locations for two different cases is given in Figure I.4.5. The colored dots represent locations of charging demands, the black

squares denote locations of charging stations. We can see that though the right-hand case has lower charging demands, the number of charging stations is approximately equal to that of the left-hand case.

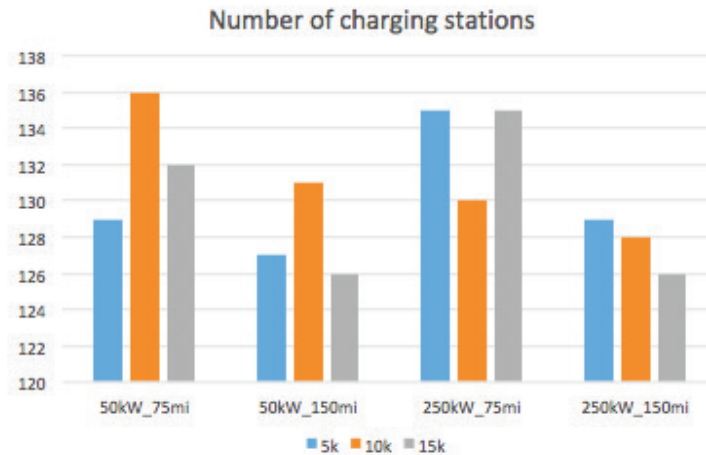


Figure I.4.4 Number of charging stations in different cases

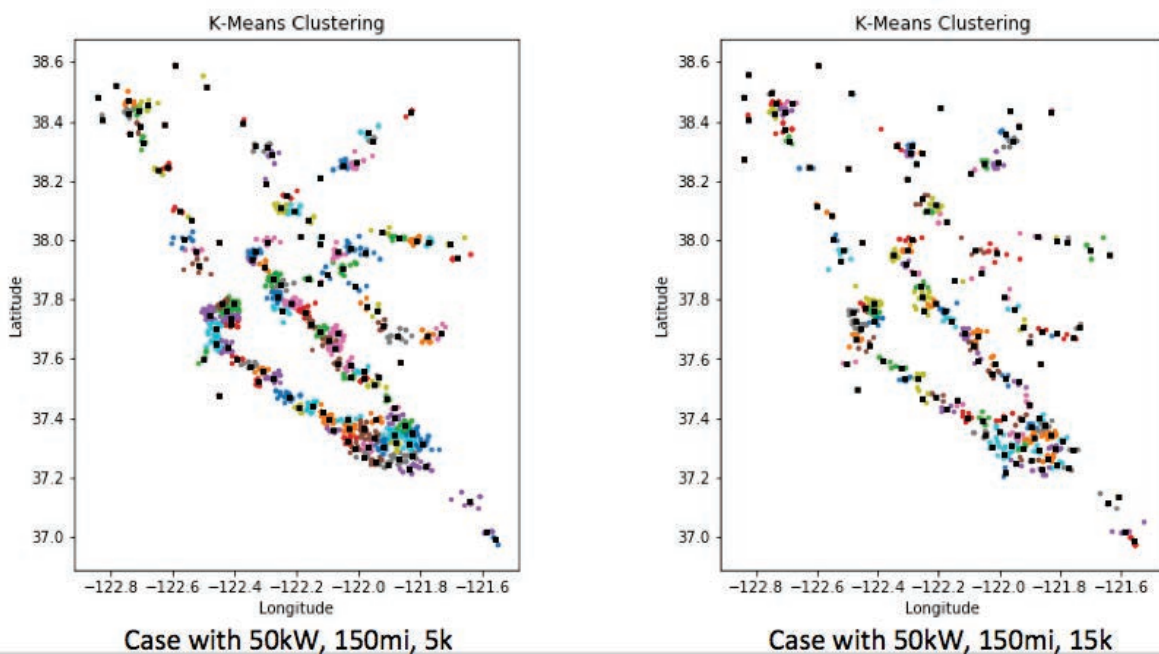


Figure I.4.5 Illustrative examples of charging station locations

In electric taxi fleet operation, the downtime from charging the vehicle can be a significant cost to the TNC due to the lost revenue that it can potentially earn for that time. This cost can be further exacerbated by prolonged charging duration due to low temperatures. A statistical method was applied on on-road data from electric taxicabs to quantify the magnitude of the effect of temperature on charging duration. The results indicated:

- The performance deterioration of a 30-minute-long DCFC charging from warm temperature (25°C) to cold temperature (0°C) can be as large as a 36% decrease in the end state of charge (SOC);

- More frequent charging is needed due to higher energy consumption from vehicle heating, ventilating and air-conditioning (HVAC) usage in cold climate;
- Either faster (higher power) chargers, more chargers, or both are needed for electric taxi operations in cold regions to maintain the level of service; and
- The performance of DCFC can vary across the United States due to the variation in regional climate.

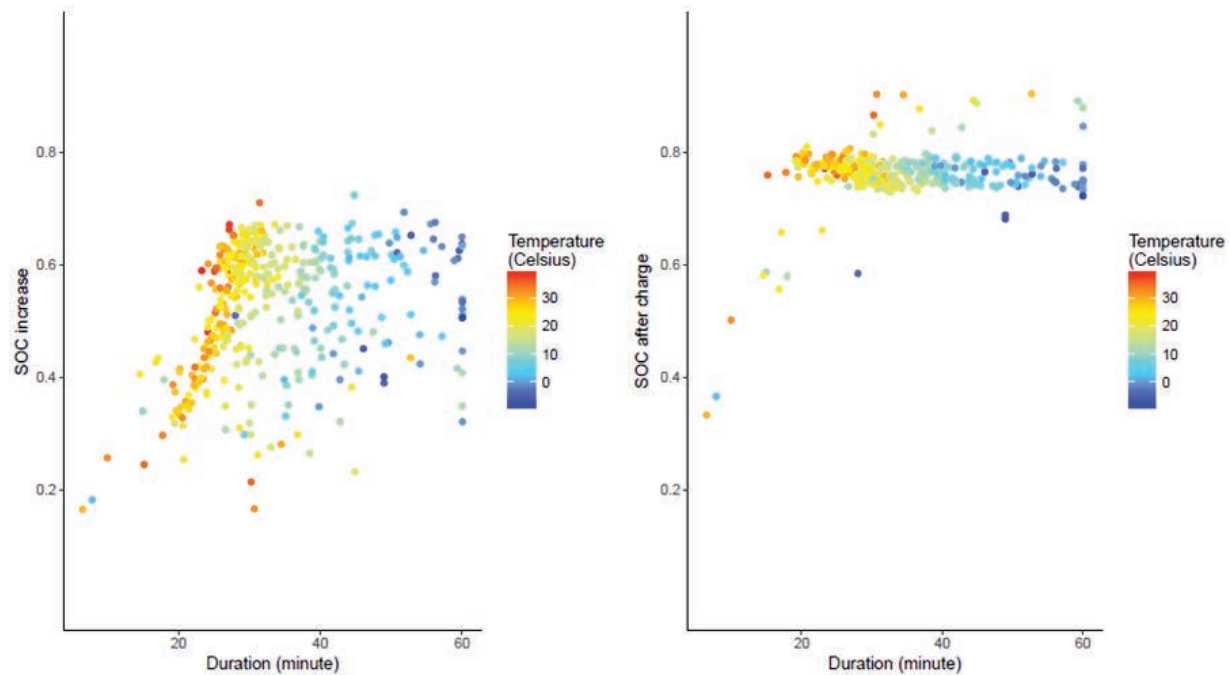


Figure I.4.6 Relationships of SOC, charge duration, and temperature

The above results indicate the charging infrastructure needs for taxi operation would vary depending on the climate of the region in which taxis are operated. Future charging stations will likely be able to charge PEVs faster and may mitigate the temperature effects, but with corresponding grid impacts.

With regard to overall project results, the detailed simulation results for two cases that both have 10 k AEVs and 50 kW rated charging power but with different vehicle driving range, i.e., 75 miles and 150 miles, are given in Table I.4.1. In both cases, we assume that the planner shall install enough number of charging stations to ensure that 80% of the EVs do not need to wait in a queue when they visit a charging station.

Table I.4.1 BEAM Output Metrics for San Francisco Bay Area Cases – PEV Taxis With 80% Service Level

METRIC	Case 1: 50 kW Charging Power and PEV Driving Range 75 Miles	Case 1: 50 kW Charging Power and PEV Driving Range 150 Miles
Passenger trips	368,847	395,679
Unique passengers	166,619	173,857
Total VMT	1,700,179	1,743,538
VMT per vehicle	174	178
Avg. Speed	30.4	30.3
Avg. Speed (VMT weighted)	33.0	33.1
Avg trip length with passenger	3.1	3.1
Avg deadhead trip length	1.3	1.3
Avg reposition trip length	2.7	2.8
Empty VMT fraction	32.9%	29.4%
Charger Number	2,159	1,936
DCFC electricity (kWh/day)	407,148	284,405
TOTAL FUEL COST (\$/YEAR)	32,726,660	27,730,364
CHARGER INVEST (\$/YEAR)	4,331,094	3,883,741
FUEL COST PER PASSENGER TRIP (\$)	0.24	0.19
CHARGER COST PER PASSENGER TRIP (\$)	0.03	0.03

From the above table, we can observe that PEVs will consume much more DC fast charging electricity with 75 miles driving range than that with 150 miles driving range. As a result, the company operating the fleet with the shorter-range vehicles has to pay a somewhat higher electricity bill per passenger trip, but in the bigger picture these are offset somewhat by lower per-vehicle costs.

With regard to overall costs of operation (fuel plus charger costs), Figure I.4.6 below shows a comparison with a gasoline internal combustion engine (ICE fleet) with gasoline at an example cost of \$3 per gallon. As shown the operation costs for an AEV fleet is considerably lower than that of an ICE-based vehicle fleet, even with a relatively high level for the estimate of needed chargers.

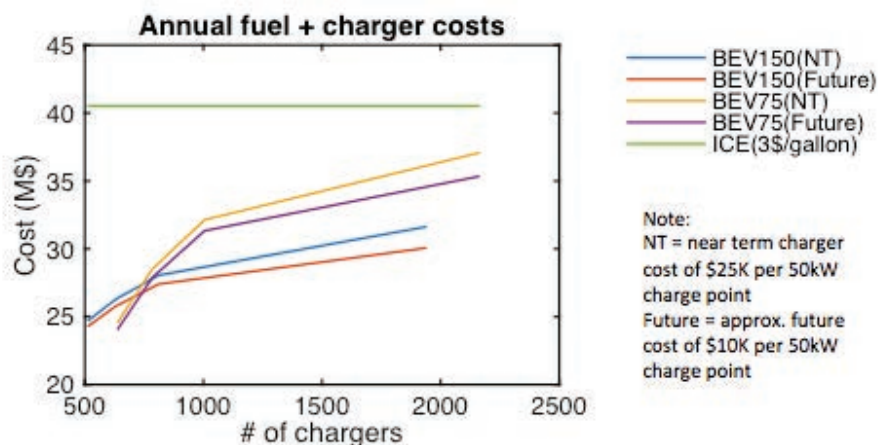


Figure I.4.6 Total operation cost comparison between ICEV and EV fleets

Conclusions

Initial findings indicate that longer driving range (larger batteries) leads to a smaller AEV fleet size, higher investment costs for the AEVs, less daytime charging demand, and lower investment costs for charging systems. Higher charging power leads to less investment in charging stations, but higher investments in grid upgrades. In addition, adopting higher power chargers will also reduce the downtime of the AEVs due to charging and enhanced PEV utilization, reducing the required vehicle fleet size to provide a given service level. Cold weather can increase the demands for PEV charging due to vehicle heating requirements and potential impacts on charging time with colder battery packs, depending on pack temperatures at the start of charging relative to ambient temperatures. Overall, we find that in terms of operating costs (fuel plus the cost of PEV chargers), these costs are typically lower than the operating costs of a comparable gasoline ICE fleet across a wide range of the number of PEV charging points in the network.

Key Publications

1. The following paper has been submitted as an outcome of the preceding FY17 AFI Task 4 that has been continued under this FY18 AFI Task 2.3:
2. Zhang, Hongcai, Colin Sheppard, Timothy E. Lipman, and Scott Moura (2019, submitted), "Joint Fleet Sizing and Charging System Planning for Autonomous Electric Vehicles," *IEEE Intelligent Transportation Systems Transactions*, Manuscript T-ITS-18-11-1073.

References

1. Neubauer, Jeremy, and Eric Wood. "The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility." *Journal of power sources* 257 (2014): 12-20.
2. Zhang, Hongcai, Zechun Hu, Zhiwei Xu, and Yonghua Song. "An integrated planning framework for different types of PEV charging facilities in urban area." *IEEE Transactions on Smart Grid* 7, no. 5 (2016): 2273-2284.
3. Krishna, K., and M. Narasimha Murty. "Genetic K-means algorithm." *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 29, no. 3 (1999): 433-439.
4. Zhang, Hongcai, Scott J. Moura, Zechun Hu, Wei Qi, and Yonghua Song. "A Second-Order Cone Programming Model for Planning PEV Fast-Charging Stations." *IEEE Transactions on Power Systems* 33, no. 3 (2018): 2763-2777.

Acknowledgements

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II SMART Mobility- Connected and Autonomous Vehicles (CAVS)

II.1 Aggregation Methods to Estimate National-Level Impacts of CAVs Scenarios (ANL, NREL, ORNL) [Task 2B]

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Start Date: October 1, 2016 End Date: September 30, 2019
Project Funding (FY18): \$1,060,000 DOE share: \$1,060,000 Non-DOE share: \$0

Project Introduction

Connected and automated vehicles (CAVs) may significantly change mobility, utility of travel, and result in large changes in transportation energy use. Under SMART Mobility and related research efforts, these potential changes are being studied using models and simulations, largely at a regional or local scale. The purpose of this task is to synthesize such research to a national level, to deliver estimated impacts of CAVs and better understand the factors on which these impacts depend. This is key to the SMART/EEMS goal to

understand overall mobility and energy efficiency opportunities at system level, accounting for behavior/economic responses.

Objectives

The objective of this task is to estimate likely levels of adoption of CAVs and impacts on mobility, energy, and costs at a national level. This is being done for scenarios of interest as identified by the SMART consortium including both low automation, modeled by adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC), and highly automated vehicles (both privately-owned and shared). In this study, technological penetration ranges from low levels representative of gradual evolution of CAV technology into the market to bounding analyses of ubiquitous CAV technologies.

Deliverables for FY 2018 were:

- A report on transferring vehicle miles traveled (VMT) simulated in regional CACC cases to the national level,
- A preliminary design of a heavy-duty vehicle component and initial implementation of a shared mobility component (for light-duty vehicles) of the CAVESIM national-level model,
- A report on CAV market penetration scenario analysis,
- Report on fuel consumption aggregation for a CACC case, and
- Initial scoping of the update of the 2016 CAVs bounding analysis.

In FY19, the task plans to deliver:

- National-level estimates of energy, mobility, and cost impacts for highly automated vehicle cases,
- A national level impacts analysis of connectivity and automation in HD/freight, and
- An update of the earlier CAV impacts bounding analysis.

Approach

Data and quantitative relationships associated with CAV adoption, travel behavior, and vehicle energy use, and their interactions, are transferred and expanded from the results of regional CAV scenario simulations. National-level models, with some regional disaggregation, are used along with methods to estimate CAVs adoption and methods for aggregating detailed regional results to give vehicle energy consumption and use at a national level. In addition, results from SMART Mobility tasks and related work outside of SMART Mobility are being reviewed to refine and extend an earlier study on the upper and lower bounds on possible impacts of CAVs on energy and mobility (Stephens et al., 2016).

The five major subtasks are:

- Estimate potential adoption of CAVs, both privately owned and shared, under different future conditions at a national level considering the heterogeneity of CAVs adopters with the MA³T-MC model. MA³T-MC model can estimate adoption of highly automated vehicles (privately owned) and shared mobility services (such as Uber and Lyft).
- Analyze changes in mobility, including metrics such as VMT and passenger-miles-traveled (PMT), and in energy use in CAVs scenarios at a national level using functional relationships developed from economic and market models that are informed by literature and by results of the SMART Mobility tasks, using the CAVESIM model. The national-level modeling framework CAVESIM was developed to produce estimates of national or regional changes in VMT and fuel use. While CAVESIM is much more

aggregated than regional meso-scale agent-based models such as BEAM or POLARIS, it is more nimble and can be used to quickly analyze a range of inputs.

- Estimate changes in travel behavior in CAVs scenarios by transferring or expanding results from regional simulations of CAVs scenarios, such as those produced from the POLARIS platform. ANL is working with the University of Illinois at Chicago to expand results of detailed POLARIS simulations of CAVs in the Chicago metropolitan area to the national level, specifically travel behavior metrics including trips per day, travel time per day, VMT, and traffic flows.
- Estimate changes in vehicle energy use in CAVs scenarios at a national level by aggregating effects of CAVs on vehicle-level energy use with VMT or traffic flow estimates. NREL is developing and validating methods to aggregate vehicle-level energy use from other SMART Mobility tasks with travel behavior estimates from ANL to give national-level changes in energy use under CAVs scenarios.
- Review SMART Mobility results and literature on the mobility and energy implications of CAVs to explore potential upper and lower bounds. ANL, working with NREL and ORNL, will review and utilize results from SMART Mobility tasks and relevant literature to refine and update the bounds on energy and mobility impacts of CAVs.

Together, these five subtasks will provide national-level estimates of changes in mobility, energy use and costs and enable better understanding of the large-scale implications of CAVs. These analyses will be performed for a range of CAVs scenarios that are being developed under SMART Mobility.

Results

In FY18 progress was made on all five subtasks.

Key results from MA3T-MC include: 1) significant consumer benefits of reduced travel time cost, reduced driving stress and reduced insurance premium (an approximate but likely underestimate of safety value), 2) reduced range anxiety of short-range BEVs due to efficient automated driving, 3) disruptive increase of personal vehicle sales due to significant consumer benefits of automated vehicles, and 4) decrease of personal vehicle sales when automated shared mobility becomes more affordable. Figure (a) and (b) show components of consumer disutility (generalized costs) of human-driven vehicles (HV) versus highly automated vehicles (AVs) of different powertrains: spark-ignition (SI) vehicle, battery electric vehicle (BEV), and plug-in hybrid electric vehicle (PHEV) in 2035 and 2050, respectively. The yellow bars in these plots show the magnitude of the generalized cost of range anxiety in short-range BEVs, which is projected to decrease due in 2050 to efficient automated driving, as in Figure b. Projected personal vehicle sales, shown in Figure I.1.2 a show disruptive increase in sales due to significant consumer benefits of automated vehicles. In contrast, the model projects decrease of personal vehicle sales when automated shared mobility becomes more affordable. With a rapid large-scale adoption of shared, highly automated vehicles, the primary mode of personal or household travel is projected to shift significantly away from other modes to shared AVs, as in Figure I.1.2 b. These results are being shared with other SMART Mobility tasks to coordinate on assumptions in different scenarios. It is anticipated that updated results will be needed as scenarios are defined, but the model is ready and can quickly provide updated estimates.

National-level analysis of a range of CAVs scenarios of highly automated vehicles using the CAVESIM model showed that national VMT and fuel use by CAVs can be expected to change significantly (tens of %) compared with manual vehicles under a range of assumptions about future CAV technology and mileage-base costs (Leiby and Rubin, 2018). The model accounts for major components of generalized costs and their interdependencies, showing how different components of generalized cost change under different conditions. This analysis considers the influence of per mile cost and per gallon fuel costs on VMT and other components of private and social costs, such as travel congestion and accident costs, fuel use externality costs, and tax interactions. Preliminary results indicate that cost incentives can be designed to allow the market development of CAVs to take advantage of their private benefits while balancing other costs and benefits.

The CAVESIM model was extended to include shared mobility, in particular sharing of rides (ride pooling). Ride pooling may be an important strategy for the improvement of Mobility Energy Productivity by limiting growth in unproductive VMT or energy use from vehicle repositioning and empty or low-occupancy vehicle travel. The purpose is to explore and represent key outcomes and tradeoffs from ride-pooling at the aggregate level.

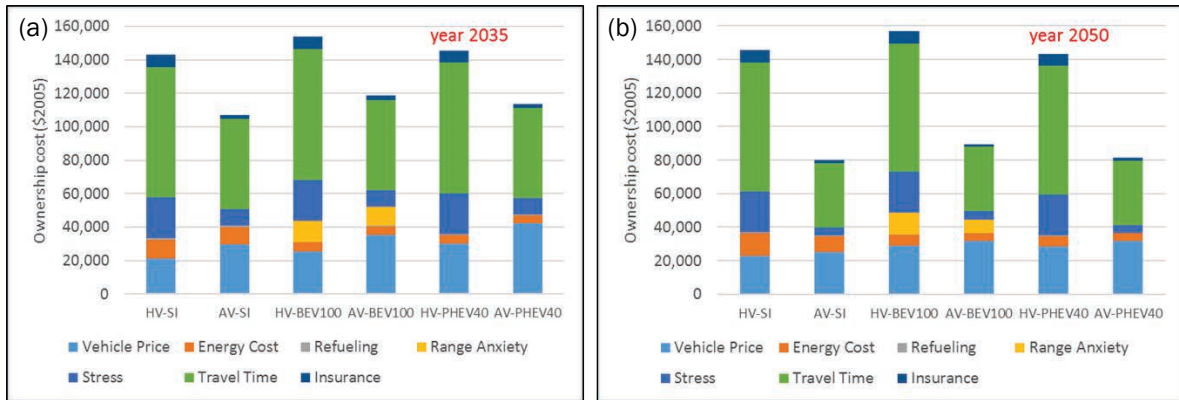


Figure II.1.1 Components of consumer utility modeled in MA3T-MC in years 2035 (a) and 2050 (b)

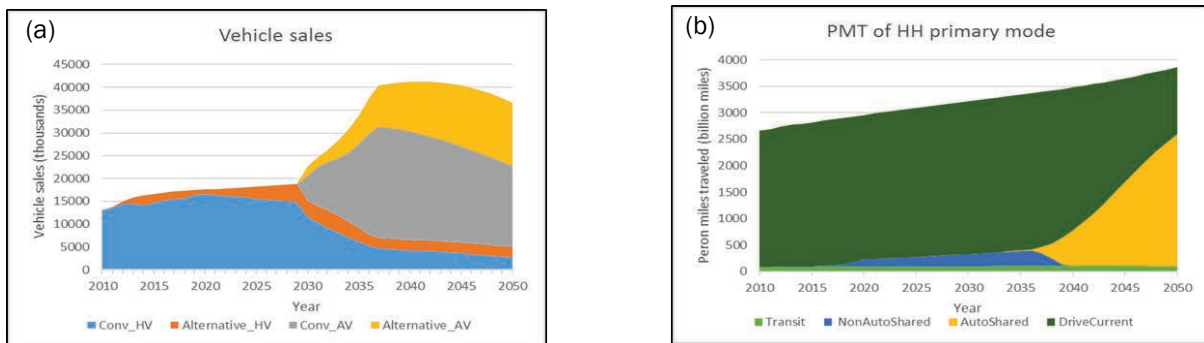


Figure II.1.2 Projected personal vehicle sales (a), and projected passenger-miles traveled by the primary mode of household (HH) travel (b)

In order to expand travel behavior results from detailed POLARIS simulations of vehicles with cooperative adaptive cruise control in the Chicago metropolitan area to the national level, transferability modeling was used. Transferability modeling successfully yielded distributions of the number of trips taken per day and the time spent traveling per day at a national level by bins or clusters of households based on the results of baseline and CACC scenario simulations in POLARIS. The method is described in (Shabanpour et al., 2018), along with results and validity checks of the baseline scenario. Multiple variations of this method were tried in order to transfer VMT results from the POLARIS simulations to the national level. However the resulting VMT projections were not yet sufficiently unreliable. Attempts were made by aggregating households to different geospatial scales, using different explanatory variables, including household or regional average demographics, land use variables, and accessibility variables, but the explanatory power of the VMT models and resulting distributions of VMT have not achieved desired accuracy. However, two alternative approaches are being developed to provide the desired changes in travel behavior from POLARIS simulations. Instead of modeling and transferring VMT for individual scenarios the change in VMT or the change in traffic flows on different links in the road network between a CAVs scenario and the baseline scenario will be modeled. If successfully validated, these models will then be applied at a national level and will supply the information

needed to combine with vehicle-level energy use analysis to give national-level energy use. Data are being prepared to apply these methods.

A national aggregation framework has been established and can accept various adoption rate inputs with respect to both alternative powertrain and CAV technology market penetration. The energy modeling approach for rolling up estimates of fuel consumption in CAVs scenarios to the national level was validated. NREL demonstrated the national aggregation framework for three cases: a baseline case (no CACC penetration), and two CACC cases in which the penetration level varied in response to different assumed technology costs and value of travel time. Vehicle-level fuel consumption and road type were available at the link level. CACC penetration levels were based on the 2017 concept paper by Shladover and Greenblatt (Connected and Automated Vehicle Concept Dimensions and Examples). This showed that the approach is tractable, flexible, and customizable, and takes into account technology penetration impacts on vehicle stock and CACC impacts on VMT distribution and fuel consumption rate matrices. The pipeline is established for running CACC impacts, and is transferable to other CAVs technologies.

For updating the CAVs energy and mobility impacts bounding study, the factors to be considered have been identified. In the last few years, SMART Mobility and external research has yielded many updated analytical results that can refine the previous bounding analysis. This year's update of the bounding study will revisit and update those factors while looking at new factors impacting energy consumption and vehicle travel. Also, the original analysis did not look at interactions between the twelve factors identified (e.g., how vehicle rightsizing and ride-sharing may interact). The CAVESIM model may provide the framework to analyze combined effects and estimate potential bounds.

Conclusions

National level modeling and aggregation methods are being enhanced and applied to estimate potential future CAV adoption levels and changes in mobility and energy use for a range of scenarios.

ORNL extended the MA³T-MC vehicle and mode adoption/use modeling to shared mobility. The model was used to produce projections of CAV penetrations. The preliminary results show that highly automated vehicles (HAVs), if perceived as safe and reliable, could disrupt personal vehicle ownership in two ways. They could increase personal vehicle ownership due to their significant consumer value from travel time cost recovery, driving stress reduction, and safety benefit. However, if HAVs enter the shared mobility sector with attractive pricing, they could lead to a decrease in personal vehicle ownership.

The CAVESIM model was used to compare potential changes in travel and energy use by automated and manually (human-driven) LDVs and to analyze influences of decentralized incentives on VMT and energy use by CAVs versus manual vehicles (Leiby and Rubin, 2018), ORNL developed and implemented a new component in the CAVESIM model to represent ride pooling (with vehicle automation) to explore implications for passenger and vehicle miles traveled, and has begun extending the CAVESIM model to a simplified representation of HDVs.

Transferability modeling was used to provide national-level distributions of trips per day and travel time under baseline conditions and for a CACC scenario, using results from POLARIS simulations. Methods to estimate changes in other mobility metrics such as VMT or traffic flows are under development.

Approaches for national-level fuel use aggregation of regional simulation results were assessed and validated : a baseline case (no CACC penetration), and two CACC cases in which the penetration level varied in response to different assumed technology costs and value of travel time.

For the planned update of the CAVs impacts bounding study, factors that will be considered in updating the CAVs energy and mobility impacts study were identified. The updated study will be broadened somewhat in scope from the previous bounds study to include not only updated bounds of effects previously considered, but also interactions between factors.

Key Publications and Presentations

1. Holden, J., H. Van Til, E. Wood, L. Zhu, J. Gonder, M. Shirk (2018) “Trip Energy Estimation Methodology and Model Based on Real-World Driving Data for Green Routing Applications.” *Transportation Research Record: Journal of the Transportation Research Board*, September, doi.org/10.1177%2F0361198118798286
2. Kontou, E., Chen, Y., Gonder, J. “Energy Consumption Analysis for Connected and Automated Mobility Systems.” July 2018 American Society of Civil Engineers (ASCE) International Conference on Transportation & Development (ICTD) lectern session
3. Kontou, E., J. Holden, M. Muratori and J. Gonder, “National-Level Energy Impacts of Cooperative Adaptive Cruise Control Systems.”, Poster for the 2018 Automated Vehicles Symposium (July 9-12, 2018)
4. Leiby, P. J. Rubin (2018) “Efficient Fuel and VMT Fiscal Incentives for Automated Vehicles,” Paper 18-04530 presented at the 97th Annual Meeting of the Transportation Research Board, Jan 7-11, Washington, DC, <https://trid.trb.org/view/1496760>.
5. Lin, Z. X, Fie, (2018) “Will Vehicle Automation Accelerate or Decelerate Electrification: Modeling Demand for Automated Electric Vehicles,” Paper 18-06046 presented at the 97th Annual Meeting of the Transportation Research Board, Jan 7-11, Washington, DC, <https://amonline.trb.org/>.
6. Shabanpour R., A. Mohammadian, J. Auld, T. Stephens (2018) “Developing a Spatial Transferability Platform to Analyze National-level Impacts of Connected and Automated Vehicles,” In *the Practice of Spatial Analysis*, Springer.
7. Stephens, T.S., J. Auld, Y. Chen, J. Gonder, E. Kontou, Z. Lin, F. Xie, A.K. Mohammadian, R. Shabanpour, D. Gohlke (2018) “Assessing Energy Impacts of Connected and Automated Vehicles at the U.S. National Level—Preliminary Bounds and Proposed Methods,” In *Road Vehicle Automation 5*, Springer.
8. Stephens, T. S., J. Auld, P. Leiby, Z. Lin, J. Gonder, E. Kontou, R. Shabanpour, A. Mohammadian, and N. Golshani “Estimating Potential Energy and Mobility Impacts of CAVs in the U.S.”, Poster for the 2018 Automated Vehicles Symposium (July 9-12, 2018)

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1. Leiby, P. J. Rubin (2018) “Efficient Fuel and VMT Fiscal Incentives for Automated Vehicles,” Paper 18-04530 presented at the 97th Annual Meeting of the Transportation Research Board, Jan 7-11, Washington, DC, <https://trid.trb.org/view/1496760>.
2. 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>.

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II.2 Traffic Microsimulation of Energy Impacts of CAV Concepts at Various Market Penetrations (LBNL) [Task 7A.1.2.]

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Start Date: October 1, 2017	End Date: September 30, 2018	
Project Funding (FY18): \$250,000	DOE share: \$250,000	Non-DOE share: \$0

Project Introduction

This project will develop traffic microsimulation tools to predict the impacts of connected and automated vehicle (CAV) on traffic and energy consumption. The CAV systems only exist today in very limited numbers in the form of prototype vehicles with limited capabilities. The status of these systems makes it impossible to do realistic field tests that can directly measure traffic or energy consumption impacts. Consequently, it is necessary to develop large-scale simulations to predict what would happen for high market penetration of CAVs. Producing meaningful and reasonable estimates of the impacts is rather challenging because it requires high-fidelity microscopic traffic models which are sensitive to the changes in vehicle behaviors, particularly the dynamic interactions CAVs with other traffic.

This report covers the simulation of CAV impact on traffic mobility and energy consumption in three aspects: (A) Traffic impact of CAVs on mixed traffic with manually driven vehicles with different market penetration and variety of scenarios; (B) Fuel Consumption Model Improvement based on MOVES (Motor Vehicle Emission Simulator); and (C) Improve Traffic Mobility for Low CAV Market Penetration Using V2I (vehicle-to-infrastructure communication) type of VSL (Variable Speed Limit). Therefore, each section of the report will contain three parts accordingly.

A. Traffic Impact of CAVs on Mixed Traffic for Intersection

Vehicle energy savings and traffic mobility improvement in real world mainly affected by many factors in three levels:

- Meso/macroscale traffic patterns:
 - Progressive market penetration of CAVs and ATM strategy will change meso/macroscale traffic pattern significantly
- Local vehicle following behavior:
 - Aerodynamic drag reduction
 - Speed variation reduction
- Vehicle level:
 - Smoothing vehicle dynamics control
 - Incorporating lower level powertrain/drivetrain characteristics, or actively controlling them

The simulation using traffic network with correct models for human driven and CAVs can be used for the evaluation of mobility and potential fuel saving benefit due to traffic pattern which is the highest level as listed above.

B. Fuel Consumption Model Improvement

For the evaluation of fuel consumption in microscopic traffic simulation with mixed traffic of manually driven vehicles and CAVs, it is necessary to have a reasonable fuel consumption model with certain input parameters which are available in simulation. Since the fuel consumption estimation in simulation can be in aggregated level like other performance parameters such as Total Travel Time, we have decided to look into a reasonable aggregated fuel consumption model for this purpose. The Motor Vehicle Emission Simulator (MOVES) model was the initial selection for this purpose. Since we have CACC truck field test data, particularly the extensive fuel consumption test data at Transport Canada Test Track with accurate fuel consumption measurement, we have used the data for validation of the MOVES model. After some level of analysis, the project team found out that the MOVES model underestimated the fuel consumption for some maneuvers and speed range, and over-estimated in others. Therefore, the project team decided to put some effort for improvement the fuel consumption model. This was the motivation of this part of work.

C. Improve Traffic Mobility for Low CAV Market Penetration Using V2I (vehicle-to-infrastructure communication) Type of VSL (Variable Speed Limit)

Simulation showed initially that when the market penetration of CACC vehicle is less than 40% (Figure II.2.1), the energy consumption increasing instead of decreasing. The reason was that, for such low market penetration, there were not many chances for CACC vehicles to get together to form platoons or CACC strings. Instead, most CACC vehicles had to operate in ACC mode. It is well-known through theory, simulation, and experiment that ACC vehicles will make traffic worse due to cumulative delays. However, the market penetration of CAV will be a lengthy and progressive process due to the large population of the status quo manually driven vehicles. Therefore, it is necessary to develop a feasible strategy which can be used in the period of low market penetration of CAVs for improving the mobility and energy saving. This is the motivation for this part of work.

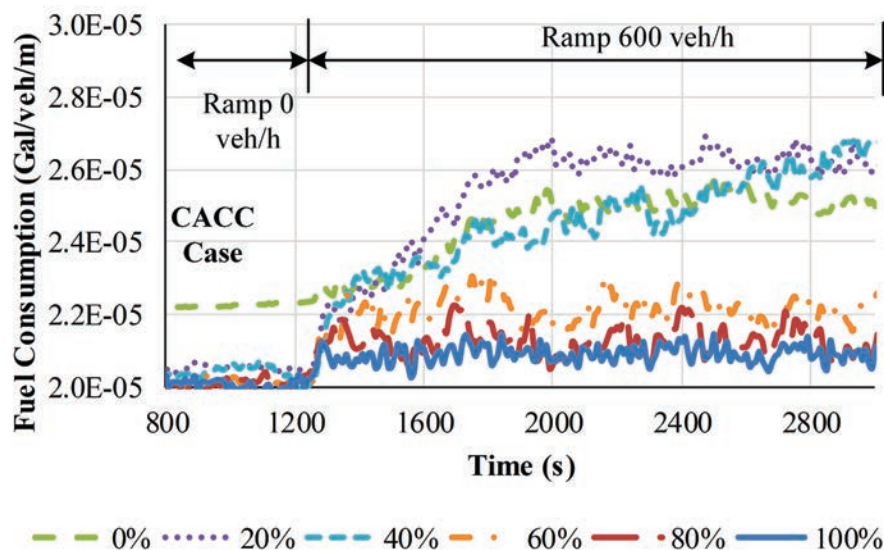


Figure II.2.1 Simulation showed that low market penetration (< 40%) of CACC vehicles caused fuel consumption increase than the status quo traffic (without CACC vehicles)

Objectives

A. Traffic Impact of CAVs on Mixed Traffic for Intersection

The objectives for this part of work include:

- Refining traffic microsimulation models that were developed under previous research projects supported by the U.S. DOT so that they can be used for wider range of CAV simulation scenarios
- Extending previous traffic microsimulation models from freeway applications to urban signalized arterial intersections, 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 and used to support subsequent national impact projections
- Producing estimates of the energy that can be saved for different levels of market penetration of CAVs operating at different levels of automation, both with and without connectivity, in specific scenarios that can be extrapolated to represent national impacts.

B. Fuel Consumption Model Improvement

The objective for this part of work was to work out a reasonable fuel consumption model which could be applied in microscopic traffic simulation to evaluate the fuel saving benefit for different scenarios and with different market penetration of CAVs in mixed traffic.

C. Improve Traffic Mobility for Low CAV Market Penetration Using V2I Type of VSL

As we mentioned before, low market penetration of V2V type of CAV could potentially make the traffic worse. The objective for this part of work is to develop a strategy with connectivity with V2I for improving traffic mobility and energy saving when the market penetration of CAVs are low, e.g. below 40%.

Approaches

A. Traffic Impact of CAVs on Mixed Traffic for Intersection

This part of work 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.

In addition to the PATH car-following and lane-changing models, this project develops a cooperative signal control algorithm that aims to maximize the intersection throughput by leveraging the CAV capabilities. The major advantage of the algorithm is that it perceives the real-time traffic condition based on the inputs from both the CAVs and fixed traffic sensors (e.g., loop detectors and radar sensors). Such an advanced traffic status perception allows it to predict the future movements of the CAVs and manually driven vehicles. The predicted information is the basis for the algorithm to compute the optimal traffic signal phasing and time (SPaT) plans that enables the intersection throughput maximization. Because the traditional traffic data sources are used to

supplement the datasets provided by the CAVs, the algorithm can be implemented at low CAV market penetration scenarios in case the intersection controller cannot gather sufficient traffic information from CAVs. In addition, the algorithm recognizes that CAVs can discharge from the queue more efficiently than the manually driven vehicles. It thus avoids assigning an equal green time to the CAVs and the manually driven vehicle. This leads to a further improved utilization of the green time resource. Moreover, the algorithm is designed to be implemented in the National Electrical Manufacturers Association (NEMA) 8-phase controllers. This makes the algorithm readily applicable at numerous real-world intersections.

B. Fuel Consumption Model Improvement

The general approach adopted for this part of work was to use field test data to validate and to improve the fuel consumption model to the level that it could reasonably reflect the actual fuel consumption for CACC truck operation. The test data was from two types of tests of 3 CACC trucks: in real-world traffic on freeway corridor and on the Transport Canada Test Track. The latter test was extensive and therefore generated significant amount of data which could be used. Besides, the test data included accurate measure of actual fuel consumption which was unique for this part of work.

In general, the key parameter to estimate energy consumption rate for a truck is Scaled Tractive Power (STP), which is considered as the required tractive power to move a truck, normalized by a constant coefficient. Scaled Tractive Power at time t (STP_t) is computed as following in [1], [2], [3]:

$$STP_t = \frac{Av_t + Bv_t^2 + Cv_t^3 + Mv_t(a_t + g \sin\theta)}{f_{scale}}$$

where

v_t : Velocity [m/s] at time t ,

a_t : Acceleration [m/s²] at time t ,

g : Gravitational acceleration [m/s²] which is equal to 9.8 [m/s²]

θ : Road grade,

M : Mass of the vehicle [metric ton], and

f_{scale} : is the scale factor equal to 17.1 [metric ton]

A , B , and C : Road-load coefficients for which calculation details are illustrated in the next section.

Once STP_t is computed, one needs to determine the vehicle operating mode. MOVES defined 23 running operating modes. The operating mode 0 represents stopped vehicles (speed < 0.45 [m/s] = 1 [mph]) and the operating mode 1 represents deceleration greater than 0.4 [m/s²]). If a vehicle does not have an operating mode of 0 or 1, its operating mode is determined based on its v_t and STP_t as demonstrated in Table II.2.1. Each cell of the figure returns an operating mode corresponding to a given speed class and a STP class. For each operating mode, an energy consumption rate can be read from Figure II.2.2.

Table II.2.1 Speed Bin Definition for MOVES Model: Determination of operating modes

		Speed class (or bin) ranges [mph]		
		1-25 (bin 1)	25-50 (bin 2)	50+ (bin 3)
VSP Class [kW/metric tons]	30+	16	30	40
	27-30		29	39
	24-27		28	38
	21-24		27	37
	18-21		25	35
	15-18		24	
	12-15	15	23	33
	9-12	14	22	
	6-9	13	21	
	3-6	12		
	0-3	11		
	<0			

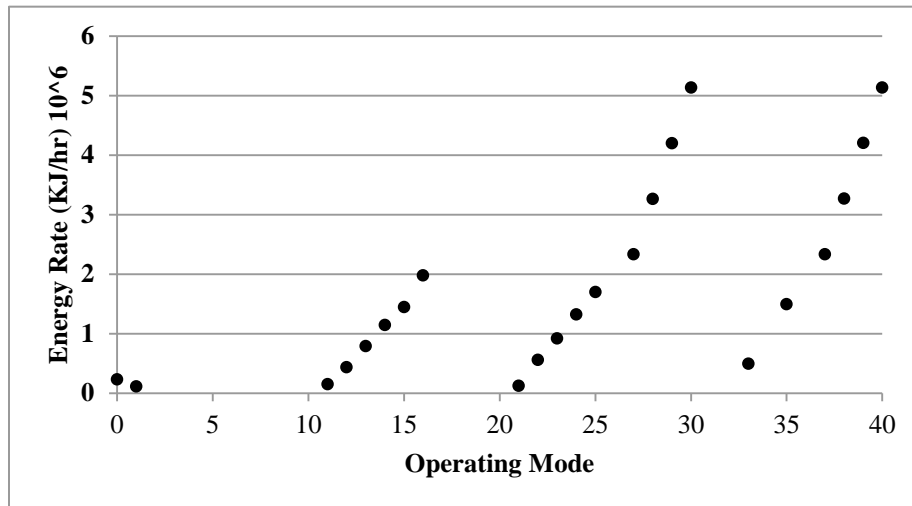


Figure II.2.2 energy consumption rates for heavy duty trucks

The fuel rate estimated by MOVES should be converted to [g/s] to compare with J-1939 bus data. The conversion is performed using the following equation.

$$\text{Fuel} = \frac{\text{Energy}}{(\text{EnergyContent})}$$

where, units of Fuel and Energy are in [g/s] and [KJ/s], respectively; and the value of Energy Content is equal to 43.488 [KJ/g] (MOVES technical Report-b, 2015).

In particular, real fuel consumption data are used to evaluate discrepancies in fuel consumption estimated by MOVES and propose a calibration model to achieve better accuracy. The study focuses on heavy duty trucks with total gross weights of 13.5, 29.5 and 50.6 metric tons during acceleration, deceleration and constant speed.

C. Improve Traffic Mobility for Low CAV Market Penetration Using V2I Type of VSL

The approach for this topic is as follows: An Active Traffic Management (ATM) strategy, particularly, Variable Speed Limit (VSL) was adopted to optimize the most downstream bottleneck flow. It is assumed that all the automated or partially automated vehicles have vehicle-to-infrastructure connection (V2I). This assumption is easy to implement since this connection can be implemented with a simple API (Application Program Interface) of cellular phones. The cellular phone can connect with vehicle with Bluetooth as most vehicles are currently doing. With those connections, the VSL determined by the Traffic Management Center (TMC) can be passed to the vehicle and used as the set-speed of the ACC vehicle. It can also be displayed to the driver and the driver can follow this set speed based on the actual traffic situation in the front. The determination of the VSL for each section is achieved by Model Predictive Control based on the speed dynamics of the second order METANET model [6]. The model can be reduced in practice in field implementation. For validation of the algorithm, a well-calibrated Aimsun microscopic traffic simulation model of I-66 East Bound inside the Beltway was used as the case study.

The design procedure can be divided into the following steps:

Step 1: Divide the freeway network into cells based on section length, number of lanes, onramp locations and traffic detector locations;

Step 2: Determine the desired speed near the most downstream bottlenecks using a simple regulator feedback control;

Step 3: Determine the VSL in other cells using Model Predictive Control approach which is discussed as follows.

Technical details are referred to [6].

Results

A. Traffic Impact of CAVs on Mixed Traffic for Intersection

The effects of the proposed signal control algorithm on traffic flow mobility and vehicle fuel consumption have been tested in a simulated arterial network where the manually driven vehicles and CAVs are modeled by the PATH car-following and lane-changing models. In the study, we focused on the evaluation of adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) systems for passenger cars. 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).

The test intersection is a four-way intersection as illustrated by Figure II.2.3. The southbound and northbound approaches are major approaches with two through lanes and a dedicated left turn lane. The westbound and eastbound approaches are minor approaches with one through and right turn lane and one left turn lane. The major approach has a traffic demand of 95% through movement and 5% left turn movement. The traffic volume of the minor approach contains 45% left turn demand, 45% right turn demand, and 10% through demand. The baseline simulation has been performed under 0% CACC case. The baseline signal adopts the actuated signal controller. The parameters of the actuated controller, including the minimum green, max green, green extension, and yellow and all red time, are shown in Figure II.2.3. Those parameters are determined

based on the method described in the Highway Capacity Manual (TRB, 2010). In addition to the baseline simulation, we also conducted analyses for scenarios of 20%, 40%, 60%, 80% and 100% CACC market penetrations with and without the cooperative signal control algorithm. We had 5 simulation runs for each scenario. Each run covered 10 minutes warm-up period and 1-hour simulation time.

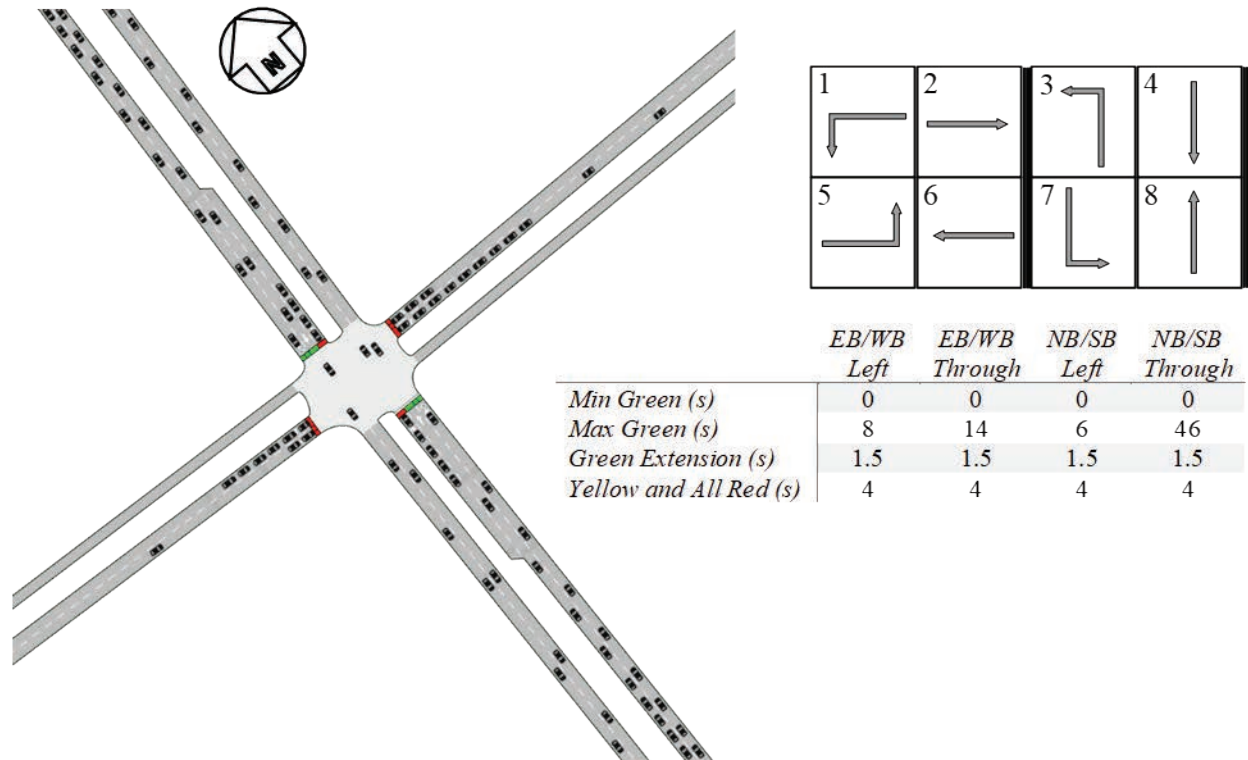
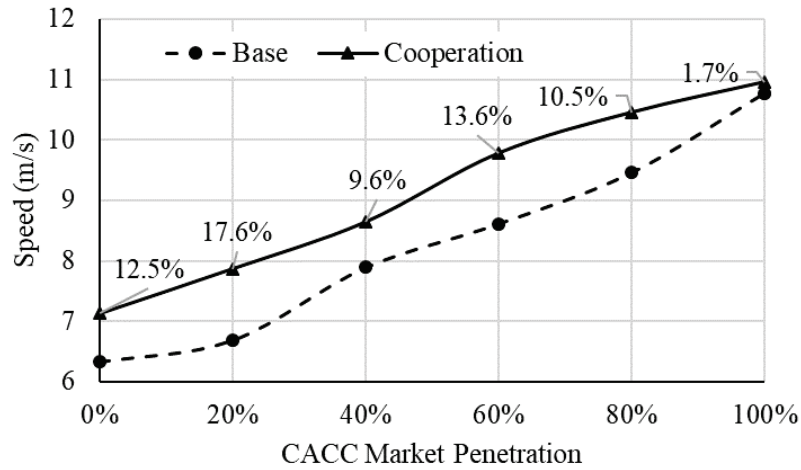


Figure II.2.3 Simulated intersection and actuated control parameters.

We aim to determine the impacts of the proposed signal control algorithm under various CACC market penetrations. In the simulation runs, the traffic demand input for the major approach was 1800 vehicles per hour and the demand for the minor approach was 350 vehicles per hour. Those inputs were the intersection capacity measured in the 0% CACC case. The average vehicle speed and average vehicle mile travelled per gallon fuel consumed (MPG) were used to depict the effects of the algorithm on both the traffic flow and vehicle fuel consumption. The vehicle speed and MPG with CACC market penetration are shown in Figure II.2.4 and Figure II.2.5. The percentages in the figures depict the improvement of the speed or MPG due to the application of the signal algorithm. Without the signal cooperation, the curve can be divided into two sections. In the first section where the CACC market penetration rises from 0% to 40%, we observe a significant increase of speed and vehicle fuel economy. This is because in the 20% or lower CACC cases, the intersection traffic is very congested under the input traffic demand. Many vehicles need to wait for more than one cycles to pass the intersection, resulting in great delay and extra vehicle fuel consumption. When the market penetration reaches 40%, the increase of the CACC strings in the traffic stream substantially increases the efficiency of the traffic flow. As a result, most of the queued vehicles can pass the intersection in one cycle, thus leading to a boost of the traffic mobility and vehicle fuel efficiency. The second section covers the cases with the CACC market penetration ranging from 40% to 100%. Within this section, the intersection performance is also improved because the number of vehicles operating in CACC strings becomes larger. But the rate of the improvement is not as high as that of the first section.



.Figure II.2.4 Average vehicle speed under various CACC market penetrations

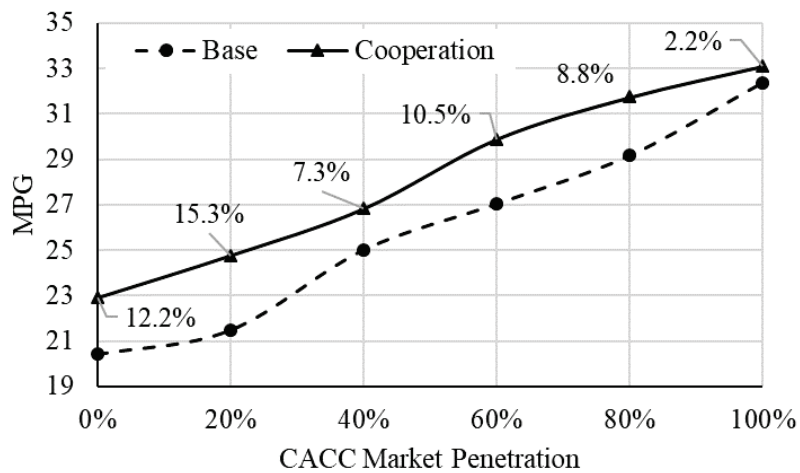


Figure II.2.5 Average vehicle mpg under various CACC market penetrations.

We have also attempted to test the performance of the algorithm under various traffic demand inputs. This analysis has been performed in the 40% and 100% CACC market penetration cases. The results can reveal the performance sensitivity under both medium and high CACC market penetration scenarios. In the tests, we have investigated the effectiveness of the cooperative signal control when the demand varies from 60% to 100% of the intersection capacity measured under the baseline actuated control case. The speed and MPG under various demands are displayed in Figure II.2.6 and Figure II.2.7.

The results show that the effects of the algorithm increase with the traffic demand input. The algorithm creates the most significant improvement when the demand in at the intersection capacity. Since such a high demand condition is often observed during peak hours, it indicates that the algorithm can be applied by the traffic agencies to relieve the congestion problems that chronically challenge the arterial traffic operation. An interesting observation is that in the 40% CACC case, the effect of the algorithm differs greatly between the 80% and 90% capacity scenario. As the traffic input rises from 80% to 90% of the capacity, the intersection traffic degrades

substantially because the default actuated controller fails to serve all queued vehicles in one signal cycle. It further leads to the rapid growth of the queue upstream from the intersection. The queued vehicles that stay idling for more than one cycles significantly reduce the overall intersection speed and vehicle fuel efficiency. On the other hand, the proposed signal control algorithm can help avoid the upstream queue propagation of the queue, thus bringing about a large improvement of the intersection performance.

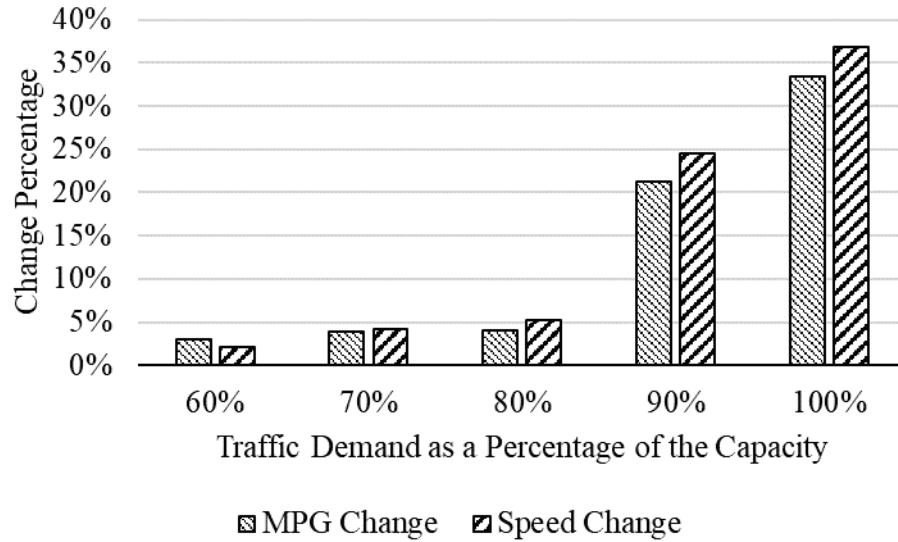


Figure II.2.6 Performance of the signal control algorithm in the 40% CACC case.

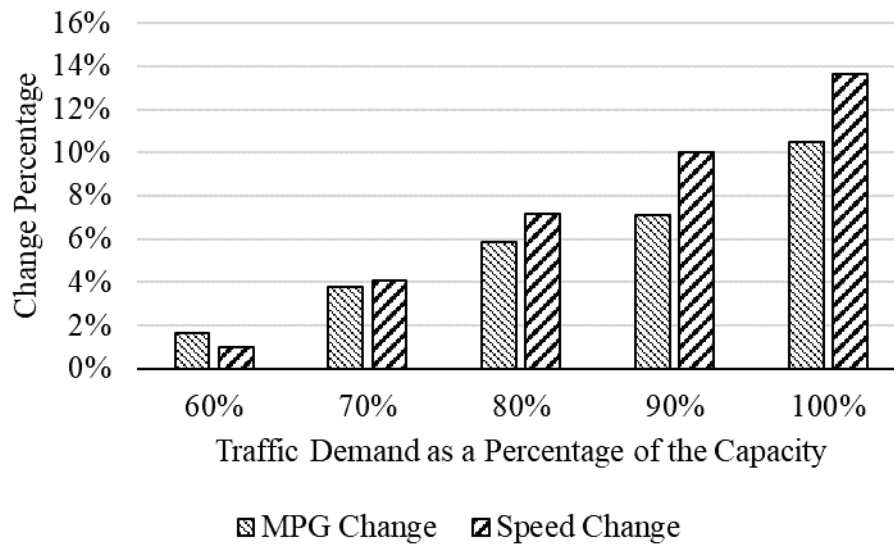


Figure II.2.7 Performance of the signal control algorithm in the 100% CACC case.

B. Fuel Consumption Model Improvement

Results showed that overall, MOVES overestimates fuel consumption during deceleration and constant speed. During acceleration, both underestimation and overestimation have been observed.

Based on the observed trends, the study develops a calibration method to reduce the discrepancy in MOVES estimates with overall R-squared of 96%. To overcome those difficulties, the following revised energy consumption model is used for the improvement of energy consumption estimation which a second order polynomial of the MOVES fuel rate:

$$f_{ob}^c = a_{0b} + a_{1b}f_{ob} + a_{2b}f_{ob}^2 + a_{3b}M$$

where

f_{ob}^c : Calibrated fuel rate in [g/s] for operating mode O and speed bin $b \in \{1, 2, 3\}$

f_{ob} : MOVES fuel rate [g/s] for operating mode O and speed bin b

M : Truck weight [metric ton]

a_{0b} , a_{1b} , a_{2b} , and a_{3b} : Coefficients of the regression model varying based on speed bin b

This model was further revised to avoid unreasonable negative value as follows:

$$f_{ob}^c = \text{Max}(f_{\text{min}MOVES,b}, a_{0b} + a_{1b}f_{ob} + a_{2b}f_{ob}^2 + a_{3b}M)$$

Then this model is used with the Least Square Fitting with the test data. The following table shows the results for the coefficients obtained for the three speed bins. The coefficients for the speed bins have been summarized in Table II.2.2.

Table II.2.2 Regression Coefficients in the Calibrated Model

Speed Bin b	a_{0b}	a_{1b}	a_{2b}	a_{3b}
1	-4.66	3.20	-0.10	0.065
2	-7.53	1.66	-0.029	0.20
3	-0.077	0.49	0.0041	0.05

C. Improve Traffic Mobility for Low CAV Market Penetration Using V2I Type of VSL

The VSL strategy have been applied to the previously calibrated microscopic traffic simulation model for I-66 East Bound (EB) inside the Beltway in Washington D. C. [4], [5]. The road geometry is depicted in Figure II.2.8. The designed MPC approach for the determination of VSL was implemented for this network in Aimsun. It was assumed that all the ACC vehicles had V2I capability in the sense that the VSL determined in TMC (or roadside) was passed to ACC vehicles and used as the *set speed*. The driver behavior of ACC vehicles was excluded. The simulation was run for different market penetration of ACC vehicles: 0%, 10%, 30%, and 50%. Each scenario was run for 10 replications (random seeds). All the performance parameters obtained were averaged over the 10 replications. The following parameters are used for the evaluation of the performance of VSL strategy:

TTT – Total Travel Time (wish to reduce)

TTD – Total Travel Distance (wish to increase)

TD – Total Delay (wish to reduce)

- Spd Var – Speed Variation (wish to reduce)
- Ave # of Stops – Average number of stops (wish to reduce)
- Flow@Syc – Flow at onramp merging bottleneck from Sycamore (wish to reduce)
- Flow@ Merge – Flow at the bottleneck of freeway merge of I-66 EB and VA 267 (Figure II.2.8)

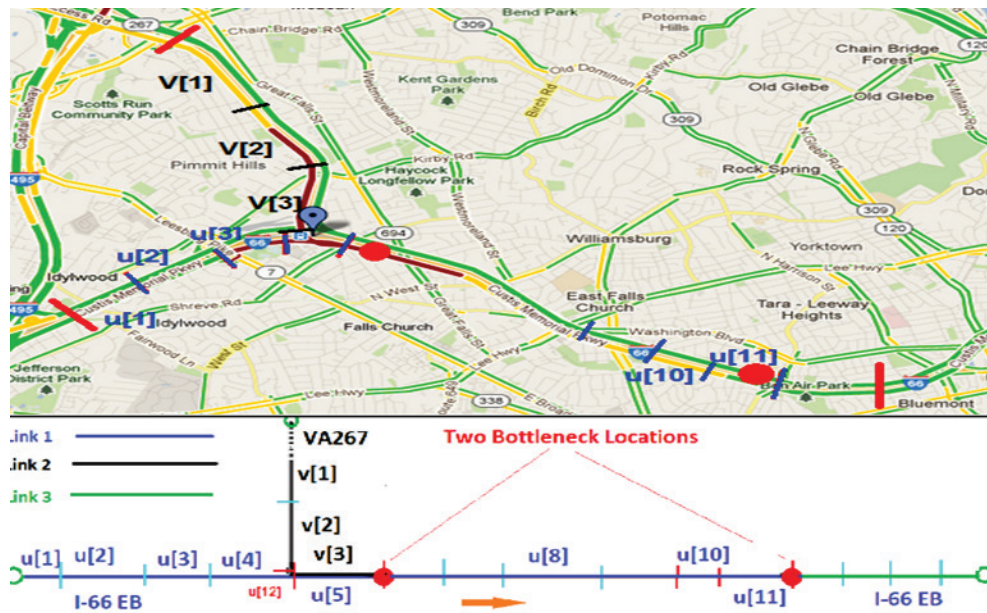


Figure II.2.8 Road Geometry for microscopic traffic simulation: I-66 EB inside the Beltway; with two bottlenecks marked with Red Spots

The following table shows the simulation results: improvement (Green) or worse (Red) with respect to the status quo traffic for market penetration of 10%, 30% and 50% respectively.

Table II.2.3 Averaged performance parameters for each market penetration level of ACC vehicles over 10 replications (random seeds)

market penetration	TTT [%]	TTD[%]	TD [%]	Spd Var [%]	Ave # of Stops [%]	Flow@Syc. [%]	Flow@ Merge [%]
10%	-6.0	0.84	-9.41	-8.41	-3.48	1.80	-0.19
30%	-6.95	1.25	-11.0	-8.3	-4.21	2.37	0.07
50%	-8.94	1.4	-13.72	-9.28	-4.90	2.24	-0.06
Mean	-7.30	1.16	-11.38	-8.66	-4.20	2.14	-0.06

It can be observed from Table II.2.3 that improvement has achieved in all aspects even with 10% market penetration of ACC vehicles. As for the two bottlenecks (marked as Red Spots) in the network, the most downstream bottleneck at Sycamore onramp is critical. The changes at the merge bottleneck were marginal. It is also note that CACC operation was not assumed here. Therefore, the potential benefit is due to V2I type of VSL only.

Conclusions

A. Traffic Impact of CAVs on Mixed Traffic for Intersection

We have developed a cooperative traffic signal control algorithm that aims to maximize the intersection throughput by using the capabilities of the CACC vehicle strings. The proposed algorithm outperforms the traditional actuated signal controllers because it recognizes that vehicles in CACC strings can utilize the green time resource more efficiently than the manually driven vehicles, and thus would assign longer green time to an approach that accommodates more CACC vehicle strings than other approaches. Due to this consideration, the CACC strings can drive through the intersection with reduced delay and increased speed. The enhancement of the CACC operation can also smooth the overall traffic flow, leading to the performance improvement of the manually driven vehicles as well.

The performance of the cooperative signal control algorithm has been tested against an actuated signal controller in a simulated four-way intersection. The test results show that the algorithm can improve the intersection speed by 1.7% to 13.6% and the average vehicle MPG by 2.2% to 15.3% when the intersection demand equals to the capacity measured in the manual vehicle only case. The most significant impact is observed in the lower CACC market penetration cases. Under those cases, the algorithm can substantially improve the traffic mobility and vehicle fuel economy by reducing or eliminating vehicles that need to wait for multiple cycles before passing the intersection. In the medium or high CACC market penetration case, the algorithm performs the best when the traffic demand is close to the intersection capacity measured under the actuated signal control. Particularly, the average speed (MPG) is increased by 13% (11%) in the 100% CACC case, and 36% (34%) in the 40% CACC case, when the demand is at the intersection capacity. The algorithm also performs well in the 0% CACC case where it completely relies on the traffic information monitored by the fixed traffic sensors. The speed and MPG can be raised by 12.5% and 12.2% in this case. This demonstrates the robustness of the proposed algorithm.

B. Fuel Consumption Model Improvement

MOVES fuel rates were compared with real fuel rate data from the J-1939 data bus for heavy duty trucks with masses of 13.5, 29.5 and 50.6 [metric tons], and then a calibration model was developed to achieve more accurate fuel rate estimates.

Comparison showed when trucks had a constant speed of 55 mph or faster, MOVES overestimated fuel rate by 26% to 88%. Similarly, MOVES overestimated fuel rate during deceleration. The relative percentage discrepancy during deceleration is more noticeable as it was as large as 206%, but in terms of absolute magnitude it was less than 1 [g/s] which may be considered as a small discrepancy. During acceleration MOVES overestimated fuel rate by 75% for mass of 13.5 [metric tons] and underestimated fuel rate by 12% and 45% for the masses of 29.5 and 50.6 [metric tons], respectively.

The calibration models were developed based on the data for class-8 diesel trucks covering a fairly wide range of truck masses between 13.5 [metric tons] to 50.6 [metric tons]. The effect of truck mass was incorporated as a parameter in the models. Each model represents one of these speed bins: 1) speed < 25 mph, 2) 25 mph ≤ speed < 50 mph, and 3) 50 mph ≤ speed. The calibrated models sufficiently reflected the trend in the real data and reduced discrepancy in fuel rate estimates with R-square of 96%. For trucks that are not comparable with class-8 diesel trucks (e.g. light duty trucks) one may use a similar approach to calibrate MOVES.

C. Improve Traffic Mobility for Low CAV Market Penetration Using V2I Type of VSL

We have found a way to improve the traffic through V2I Variable Speed Limit (VSL) for low market penetration of CACC vehicles. This approach uses currently available road traffic detector and ACC vehicle (with V2I capability) information to calculate a VSL for each small section of the freeway corridor. Such VSL is then passed back to the ACC vehicle through V2I and used as the set-speed. Simulation showed that Total Travel Time (TTT) could be reduced by 6~7% and speed variation could be reduced by 8% when the market

penetration of ACC was about 10~30%. This initial study has not evaluated fuel saving benefit yet, which could be conducted in future research.

Key Publications

1. H. Liu, X.-Y. Lu and S.E. Shladover, “Traffic Signal Control by Leveraging Cooperative Adaptive Cruise Control (CACC) Vehicle Platooning Capabilities”, paper to be submitted to *Transportation Research Part C*
2. H. Liu, X.-Y. Lu and S.E. Shladover, “Traffic Signal Cooperation for Enhancing Cooperative Adaptive Cruise Control (CACC) Vehicle String Operations”, under second review by Transp. Research Record.
3. H. Ramezani, S. E. Shladover, X. Y. Lu, and O. D. Altan, Ph.D., Micro-Simulation of Truck Platooning with Cooperative Adaptive Cruise Control: Model Development and a Case Study, TRB Annual Meeting, Washington D. C., Jan 7-11 2018; accepted by *TRB Journal of Transportation Research Record*
4. H. Ramezani, X. Y. Lu, and Steven Shladover, Calibration of Motor Vehicle Emission Simulator (MOVES) using Real Heavy-Duty Truck Data, accepted TRB Annual Meeting, Jan. 2019, Washington, D. C.
5. H. Ramezani, X. Y. Lu, and Steven Shladover, Calibration of Motor Vehicle Emission Simulator (MOVES) to Incorporate Effect of Truck Platooning, accepted for TRB Annual Meeting, Jan. 2019, Washington, D. C.
6. X. Y. Lu and S. Shladover, MPC-Based Variable Speed Limit and its Impact on Traffic with V2I Type ACC, accepted by IEEE Conference on Intelligent Transportation Systems, Nov 4-7, 2018, Maui, Hawaii,

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5. X. Y. Lu, S. Shladover, I. Jawad, R. Jagannathan, and T. Phillips, 2015, A novel speed-measurement based variable speed limit/advisory algorithm for a freeway corridor with multiple bottlenecks, *Transportation Research Record*, #2489, p86–96; DOI: 10.3141/2489-10
6. X. Y. Lu and S. Shladover, MPC-Based Variable Speed Limit and its Impact on Traffic with V2I Type ACC, IEEE Conference on Intelligent Transportation Systems, Nov 4-7, 2018, Maui, Hawaii

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II.3 Impact of CAVs on Energy, GHG, and Mobility in a Metropolitan Area (ANL) [Task 7A.1.3]

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Start Date: October 1, 2017	End Date: September 30, 2018	
Project Funding (FY18): \$635,000	DOE share: \$635,000	Non-DOE share: \$0

Project Introduction

In this task, we sought to estimate the impact of connected and autonomous vehicles (CAVs) on energy and mobility in the transportation sector in a region for different vehicle technologies. In the absence of any data related to CAVs, the approach of relying on rational assumptions, behavioral models, and scenario analysis is the best option for understanding the impacts. As part of this task, we identified three key components that needed to be developed (or advanced) and then integrated with POLARIS, our transportation system simulation software. We then used the updated POLARIS tool to evaluate the energy and mobility outcomes of the new mobility technologies in the context of the Bloomington, Illinois, region. Key highlights of the research have shown that depending on vehicle and AV technology characteristics and behavioral assumptions, estimated fuel consumption reduction by 2040 as high as 74% can be achieved. This occurs even under a 64% increase in vehicle miles traveled (VMT), when vehicle electrification and efficiency gains are accounted for. However, energy consumption reductions could be as low as 6% in scenarios where low vehicle electrification and other advanced technology penetration is coupled with high AV penetration and no unloaded mileage pricing, in which case VMT could increase up to 85%.

Objectives

The objective of this task is to quantify the energy impact of CAVs technologies at the transportation system level.

- The first component to be developed models households' travel behaviors in the context of a privately owned autonomous vehicles (AVs) environment, where the households are trying to minimize their costs and be flexible in terms of start and duration of their activities.
- The second component is a model that coordinates vehicle platoons (given the demand for vehicle travel) and a traffic simulator that could simulate the coordinated platoons and their movements.
- The third component involves generating fundamental diagrams of traffic flow for different market penetration levels of CAVs; determining these diagrams are essential information when simulating traffic.
- Because POLARIS is the main transportation simulation framework we use, the models will be incorporated into it to enable us to analyze the CAV scenarios of interest.

Approach

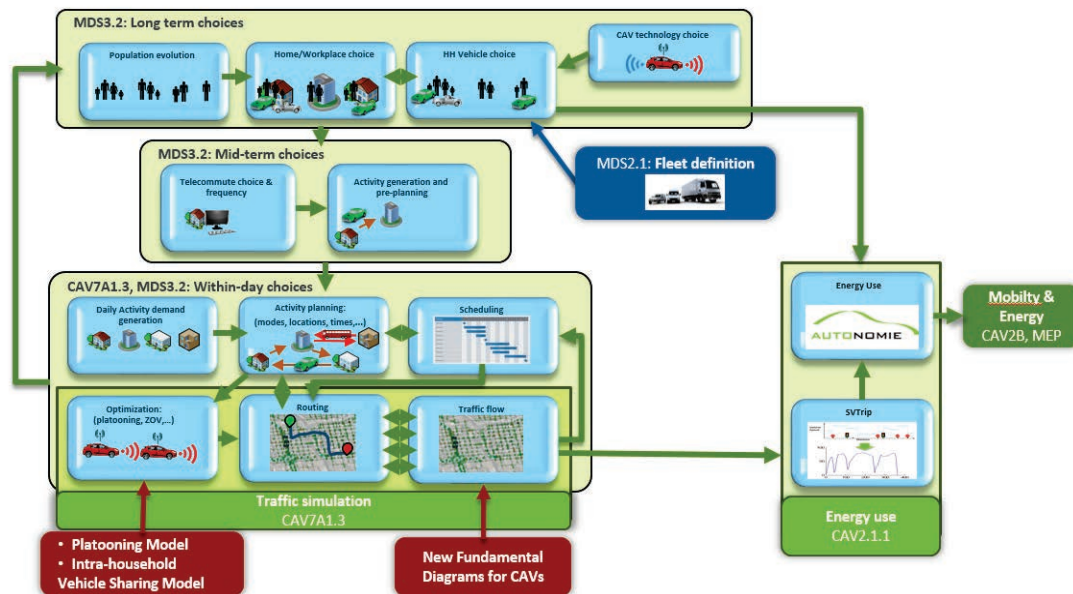


Figure II.3.1 POLARIS modeling process with CAV improvements highlighted

The approach that we adopted to achieve the objectives of this task involved development of the behavioral models and then implementing them in POLARIS, our main simulation tools, for scenario analysis. For the first two objectives, optimization models were identified as the best available tool to simulate rational individuals' behavior. For the platooning simulation, the model developed by Argonne researchers in the Mathematics and Computer Science (MCS) Division was adopted and integrated with POLARIS. The model tries to form platoons of vehicles while minimizing their energy use. POLARIS sends the demand for travel (by platooning-enabled vehicles) to the algorithm, and it coordinates the vehicles' movements in platoons. Then POLARIS uses the results to update the vehicles' movements. The intrahousehold, vehicle-sharing model is also an optimization model that our team developed. The model tries to minimize generalized costs of travel of each household when AVs are available. For the third objective, we consulted Texas A&M researchers for use of their advanced deep learning algorithm and their microsimulator so we could generate the fundamental diagrams and then incorporate them into the POLARIS traffic simulator. Figure II.3.1 highlights the new components and show how they interact with existing POLARIS components.

The Intrahousehold, Autonomous Vehicle-Sharing Optimization Model

One of the possible scenarios for the future of transportation/vehicle ownership is adoption of privately owned Level 5 AVs, which could become ubiquitous or at least adopted by a percentage of households. To model the travel behaviors of these households, an optimization model was developed that takes the households' travel plans and schedules, along with transportation network information, as inputs and generates the AVs' travel plans. The mixed integer programming (MIP) optimization model finds the optimal number of Level 5 AVs that a household needs, given its activities and schedules. It could be considered a Vehicle Routing Problem with Time Window that is tailored to a household with Level 5 AVs and the household members' travel needs. The model also schedules the optimal AV trips, while considering vehicle/ride-sharing, travel to home/parking, flexibly in timing, taxis, and various travel costs, as well as any charges for zero-occupancy travel. The travel-related costs include energy, value of time, vehicle ownership, parking, and taxi fares. The optimization model has been integrated with POLARIS and is called upon whenever a household is determined to have privately owned AVs. The results of the optimization model (encompassing the AVs' travel plans including zero-occupant vehicle [ZOV] trips) are also simulated in the POLARIS traffic simulator.

A case study was conducted for Bloomington, Illinois, for the base year (2015), short-term view (2025), and long-term view (2040), with details shown in Figure II.3.2. The demand assumptions included high CAV demand (with a marginal cost of \$5,000, high flexibility) and low CAV demand (with a marginal cost of \$15,000, low flexibility), where the value of travel time savings is 50% of base (~seated, high-quality transit). Data were provided on the base- and forecast-year land use, as well as population and employment provided by the MPO (Metropolitan Planning Organization) and vehicle distribution provided by Polk/IHS (Information Handling Services) registration data for the base year. The CAV technology Level 4 (i.e., with no ZOVs) and Level 5 (with ZOVs) were considered in the scenarios.

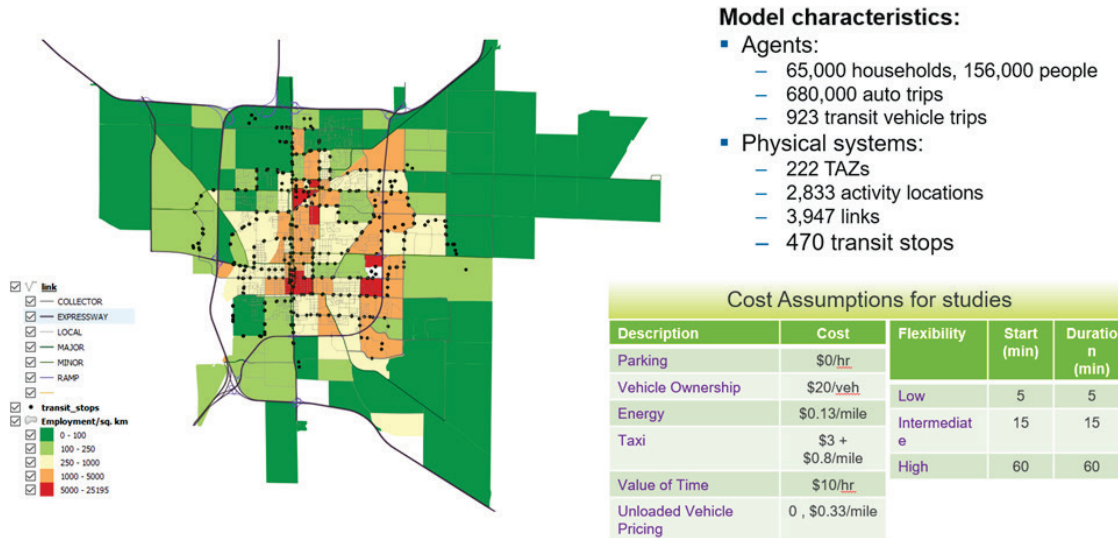


Figure II.3.2 Scenario design for Bloomington case studies

A summary of the results is presented in Table II.3.1 and depicted in Figure II.3.3. They demonstrate that ZOV trips could increase single-occupancy vehicle (SOV) trips by an additional 27% (for low CAV penetration rates) and 39% (for high CAV penetration rates) over baseline, whereas introducing ZOV pricing of \$0.1 per mile could reduce the impact to some degree (to 25% and 35%, respectively, for the low and high rates). Fuel consumption is reduced by up to 75% for the low CAV penetration rate at 2040 in comparison to baseline (in the high-tech case) and by up to 71% in the high CAV penetration rate, depending on the CAV accessory load. However, in the low-tech cases, fuel reductions can be as low as 6% from baseline (essentially no change from current fuel use despite vehicle powertrain advances). We also found that ZOV charging could further reduce fuel consumption by 1% and 5%, depending on vehicle technology and CAV penetration.

Table II.3.1 Comparison to baseline for Levels 4 and 5 CAVs for various fleet assumptions

Impacts of population growth					Impact of vehicle technology on fuel use (gallons)					
Scenario	Trips	VMT	VHT	Avg. Speed (mi/hr)	Tech-low			Tech-high		
					600W ¹	1000W	2500W	600W ¹	1000W	2500W
Baseline (2015) ²	475,149	1,645,855	63,178	26.1	64,428			64,428		
2025_base	523,806	1,851,744	71,440	25.9	48,259			34,530		
2040_base	563,131	2,004,973	80,090	25.0	31,493			11,243		
(% Δ from 2015 baseline)					Impact of vehicle technology on fuel use (gallons)					
Impacts of level 4 CAV					Tech-low			Tech-high		
Scenario	Trips	VMT	VHT	Avg. Speed (mi/hr)	600W ¹	1000W	2500W	600W ¹	1000W	2500W
2025_base	10%	13%	13%	-1%	-25%			-46%		
2025_cav-low	11%	16%	11%	5%	-22%		-19%	-43%		-40%
2025_cav-high	11%	20%	14%	6%	-19%	-17%	-12%	-41%	-40%	-34%
2040_base	19%	22%	27%	-4%	-51%			-83%		
2040_cav-low	20%	32%	31%	1%	-46%	-45%	-41%	-80%	-80%	-77%
2040_cav-high	20%	36%	37%	0%	-43%	-41%	-33%	-79%	-78%	-74%
(% Δ from 2015 baseline)					Impact of vehicle technology on fuel use (gallons)					
Impacts of level 5 CAV					Tech-low			Tech-high		
Scenario	Trips	VMT	VHT	Avg. Speed (mi/hr)	600W ¹	1000W	2500W	600W ¹	1000W	2500W
2040_cav-low	46%	64%	86%	-12%	-32%	-30%	-23%	-74%	-73%	-68%
2040_cav-high	58%	85%	120%	-16%	-22%	-19%	-6%	-69%	-67%	-60%
2040_cav-low-ZOV charge	44%	61%	80%	-11%	-33%	-31%	-24%	-75%	-74%	-70%
% Δ from 2040_cav-low	-1%	-2%	-3%	1%	-1%	-2%	-2%	-4%	-4%	-4%
2040_cav-high-ZOV charge	54%	79%	112%	-15%	-24%	-21%	-9%	-71%	-69%	-62%
% Δ from 2040_cav-high	-2%	-3%	-4%	1%	-3%	-3%	-3%	-5%	-5%	-5%

1. CAV accessory load is 0 for the baseline cases
 2. Vehicle low tech and high tech scenarios are the same for baseline

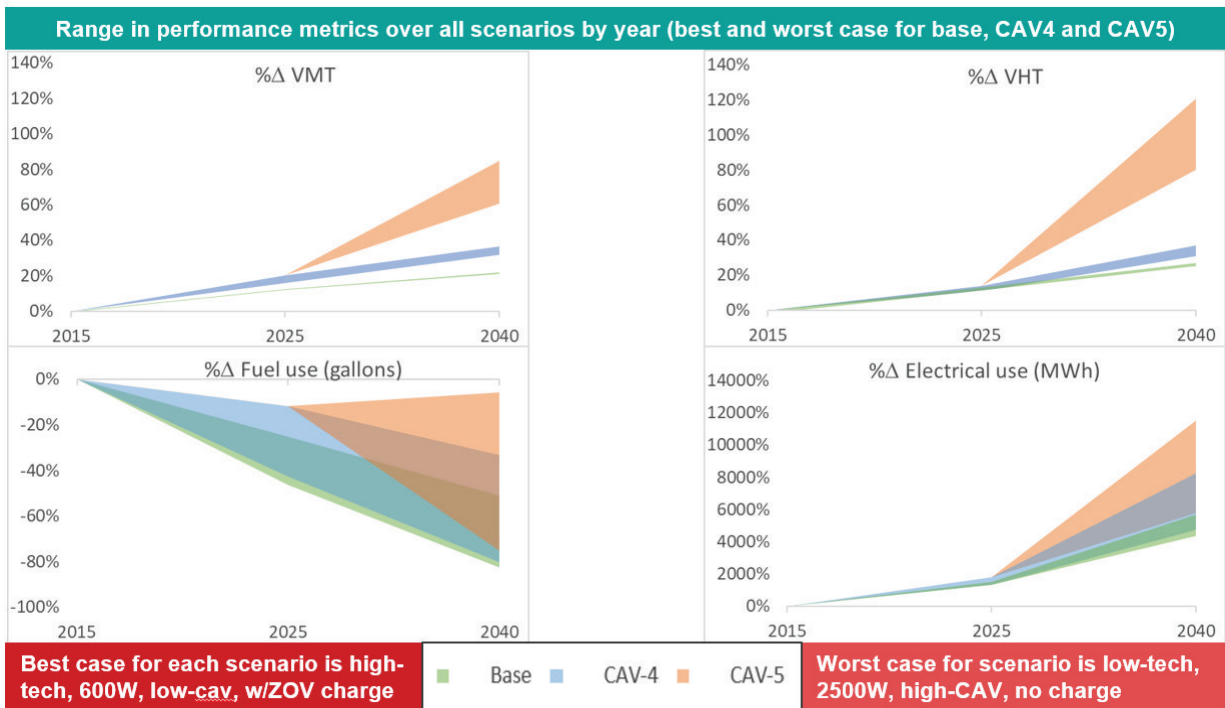


Figure II.3.3 Best and worst case performance metrics over time under privately owned, Level 4/5 CAV scenarios

The Coordinated Platooning Model

One of the expected benefits of AVs is their platooning capabilities; however, vehicle platooning has been studied mainly in terms of one platoon. To analyze the energy impact(s) of platooning vehicles at the regional level, we adopted an optimization model developed by Argonne’s MCS Division. The optimization model schedules platoons’ formation and dissolution given the demand for vehicle travel. To correctly simulate the

platoons’ movements, the POLARIS code also needed to be updated to accommodate changes in travel times and trajectories. During the past year, POLARIS was first manually linked to the optimization model (involving many pre- and post-processing steps), and then it was enhanced so it would automatically and continuously call the optimization model (with the POLARIS vehicles’ trajectories as inputs) and also update their movements according to the optimization model results. Because optimization models are computationally intensive and tax computing resources, a clustering algorithm was also developed to group vehicles into multiple bins and thereby improve performance. This approach breaks the big problem into smaller ones, which, in turn, reduces the size of the optimization model problems and improves performance. In addition, Autonomie was updated to take into account the reduction in energy consumption attributable to the reduction in aero drag on vehicles in platoon.

A couple of case studies were conducted for a sample of the Detroit region in addition to the Bloomington, Illinois, analysis (Table II.3.2).

Table II.3.2 Bloomington, Illinois, mobility and energy impacts resulting from platooning

Penetration Rate	LOW (Cost = \$2,500)		
	No Platoon	300	600
Wait Time (second)			
Total Trips	452,873	453,555	456,580
% of platooning capable trips	-	35.3%	35.3%
% of Platooning trips	-	2.6%	4.5%
Total VMT	1,938,903	1,936,901	1,947,523
%VMT in Platoon	-	1.3%	2.6%
Fuel Consumption(kg)	152,83,	151,950	151,220
Fuel Consumption per mile(gr/mile)	78.8	78.4	77.6

Preliminary results indicate that with increases in wait times, the chances for platooning to occur increase significantly. In addition, given the assumptions and models used for estimating reduction in drag coefficients, the savings on energy consumption increases by 0.5% and 1.5% for 60 seconds and 200 seconds, respectively.

Traffic Improvement

In this project, we contracted with Texas A&M researchers to take advantage of their deep learning models developed for controlling CAVs, as well as their microsimulator for generating a new series of fundamental diagrams of traffic flow and speed-density curves, which are the most important data for mesoscopic traffic simulation. The generated fundamental diagrams will be incorporated into POLARIS traffic flow models to develop a realistic representation of traffic flow dynamics in the presence of CAVs. To make the diagrams more general but still accurate, for the Chicago network, the highways are clustered into 60 spatiotemporal groups that share similar traffic behaviors.

The diagrams have been generated for the Chicago region at different CAV market penetration rates, and a case study was conducted for Bloomington, Illinois. Figure II.3.4 shows how increasing the market penetration rate of CAVs affects the flow-density relationships. Network fundamental diagram (NFD) results () also indicate that higher penetration rates of CAVs can result in less congestion and less scatter in the fundamental diagram.

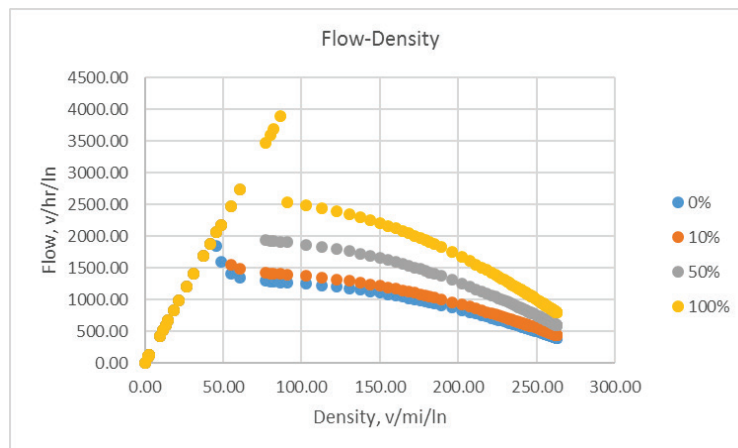


Figure II.3.4 Flow-Density Relationship for M=45.

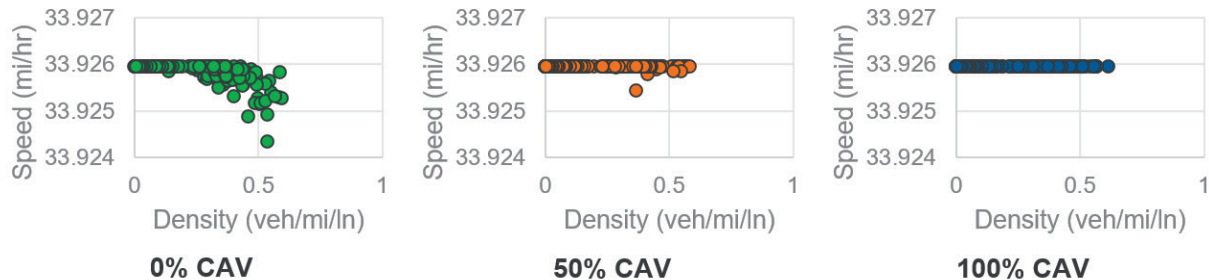


Figure I.3.5 NFD analysis for the Bloomington, Illinois, model

Two optimization models have been developed to simulate advanced features of autonomous vehicles. The optimization models have been coded in C++ and integrated with POLARIS to be used with different scenario analyses when AV simulation is involved. The POLARIS model has been significantly enhanced in order to better simulate individuals' travel behaviors and traffic involving the use of CAVs. Both intrahousehold vehicle sharing and coordinated platooning (forming and dissolution) models have been developed, and new fundamental diagrams of traffic flow have been generated for various market penetration rates for CAVs. The models have also been incorporated into POLARIS, and various scenarios were analyzed, which demonstrates how platooning and privately owned vehicles could deliver impacts on energy consumption.

Conclusions

This project has combined research on household-level vehicle sharing and traveler behavior, traffic flow changes under CAV technologies and coordinated platooning algorithms enabled by vehicle connectivity into the POLARIS regional transportation system simulator. This is done in order to explore impacts that privately owned autonomous vehicles could have on regional mobility and energy use. The research has demonstrated how privately owned autonomous vehicles could increase overall travel due to reduced travel burden (for both partial and full automation) as well as due to vehicle repositioning (in fully automated vehicles). We also evaluated how these changes interact with vehicle technologies by analyzing a range of additional accessory load requirement for CAV in both low-technology (business-as-usual) and high-technology (VTO program success) cases. Overall, we found that in business-as-usual vehicle technology cases, fuel consumption reductions range from 6% to 33% from baseline, under VMT increases of 85% and 61% respectively, while advanced vehicle technology cases show fuel use reductions up to 75% with VMT increases of 61% to 64%. Additionally, we found that ZOV pricing could mitigate some of the impact of ZOV by reducing VMT by up to 3% and fuel use up to 5%.

Key Publications and Presentations

1. Javanmardi, Mahmoud, Joshua Auld, and Omer Verbas. “Analyzing Zero Occupancy Vehicles’ Traveled Miles in a Shared Private Mobility Environment Using a Multi Autonomous Vehicles Assignment Model.” Presentation at the 7th Innovations in Travel Demand Modeling, Atlanta, Georgia, USA, June 24–27, 2018.
2. Javanmardi, Mahmoud, Ehsan Islam, Joshua Auld, and Jeffrey Larson. “A Case Study Analysis of Energy Consumption Potential of Coordinated Platooning in Urban Networks.” Accepted for presentation at the 98th Annual Meeting of the Transportation Research Board, Washington, D.C., USA, January 13–17, 2019.
3. Javanmardi, Mahmoud, Joshua Auld, and Krishna Murthy Gurumurthy. “Intra-Household Fully Automated Vehicles Assignment Problem, Model Development and Case Study.” Accepted for presentation at the 98th Annual Meeting of the Transportation Research Board, Washington, D.C., USA, January 13–17, 2019.
4. Javanmardi, Mahmoud, and Joshua Auld. “Analyzing the Impact of Zero Occupancy Vehicle Miles Traveled in a Shared Private Mobility Environment.” Accepted for presentation at the 15th International Conference on Travel Behavior Research, Santa Barbara, California, USA, July 15–20, 2018.
5. Auld, Joshua, Omer Verbas, Mahmoud Javanmardi, and Aymeric Rousseau. 2018. “Impact of Privately-Owned Level 4 CAV Technologies on Travel Demand and Energy.” *Procedia Computer Science* 130: 914–919. doi: 10.1016/j.procs.2018.04.089.
6. Khajeh-Hosseini, Mohammadreza, Alireza Talebpour, Mahmoud Javanmardi, Joshua Auld, and Yalda Rahmati. “A Two-Stage Clustering Approach to Study Network Traffic Dynamics.” Accepted for publication at *Journal of Transportation Engineering, Part A: Systems* (forthcoming).
7. Khajeh-Hosseini, Mohammadreza, Alireza Talebpour, Mahmoud Javanmardi, Joshua Auld, and Yalda Rahmati. “A Two-Stage Clustering Approach to Study Network Traffic Dynamics.” Paper presented at the 97th Annual Meeting of the Transportation Research Board, Washington, D.C., USA, January 7–11, 2018. Published in *A Two-Stage Clustering Approach to Study Network Traffic Dynamics* (forthcoming).

II.4 Modeling CAVs transition dynamics and identifying tipping points (NREL) [Task 7A.1.4]

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Start Date: January 1, 2017	End Date: September 30, 2019	
Project Funding (FY18): \$330,000	DOE share: \$330,000	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. This capability uses 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 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 key elements 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. During FY 2018, we obtained results of the Whole Travel Survey from Lawrence Berkeley National Laboratory (LBNL) that we will incorporate to refine our characterizations of various cohorts of travelers. We developed plans to work with Los Alamos National Laboratory (LANL) to improve targeting of sensitivity analysis designs towards outcomes of greatest interest. We participated in inter-laboratory coordination discussions (SMART Workflow Task Force and Scenario Planning), and as those discussions yield consensus assumptions for key CAVs and other mobility factors these will be incorporated into the analyses under this task.

Hypothesis Development

Hypothesis development provides organizational structure for our methodological and analytic work, establishing priorities for the improvement of our understanding of CAVs opportunities. During FY 2018, we continued to test hypotheses about CAVs deployment scenarios. The current status of the analytic hypotheses is summarized here:

Table II.4.1 Hypotheses

Hypothesis	Test	Status
Synergies between technology pathways, CAVs concepts, and adoption behavior lead to multiple potential “end states.”	Model results	Confirmed
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	Confirmed

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. During FY 2018, we updated the data to incorporate the new National Household Travel Survey (NHTS).

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. During FY18, we extended the conceptual model to encompass commercial delivery systems, with plans to implement these into the existing functional model during FY19.

During FY18 we used the CAVs tipping point model to develop sensitivity analyses exploring CAVs deployment scenarios and energy outcomes. A selection of these results is presented below.

Results

Based on preliminary data, we performed multiple sensitivity analyses totaling hundreds of thousands of simulations on parameters related to stakeholder actions and preferences, travel choice, and CAVs characteristics such as occupancy and dead-head miles. In one such analysis, we ran approximately 13,000 simulations that varied these parameters over plausible ranges of values. Additional scenarios explored the strength of feedbacks and causal influences in the model and identified sensitivities to other input parameters. The results show the potential that various stakeholders could slow CAVs growth as bottlenecks in the system and the system-wide fuel use under a range of behavioral and financial parameters.

CAV adoption faces a complex landscape of overlapping stage gates. Figure II.4.1 summarizes the frequency (among the scenarios) of particular stage gates becoming the bottleneck limiting the availability of L4 automated taxis. In many cases, lack of consumer interest or lack of completion of R&D blocks availability. In scenarios where those two stages have been overcome, factors such as infrastructure readiness, vehicle manufacturing, or regulatory approval impose delays but not permanent bottlenecks.

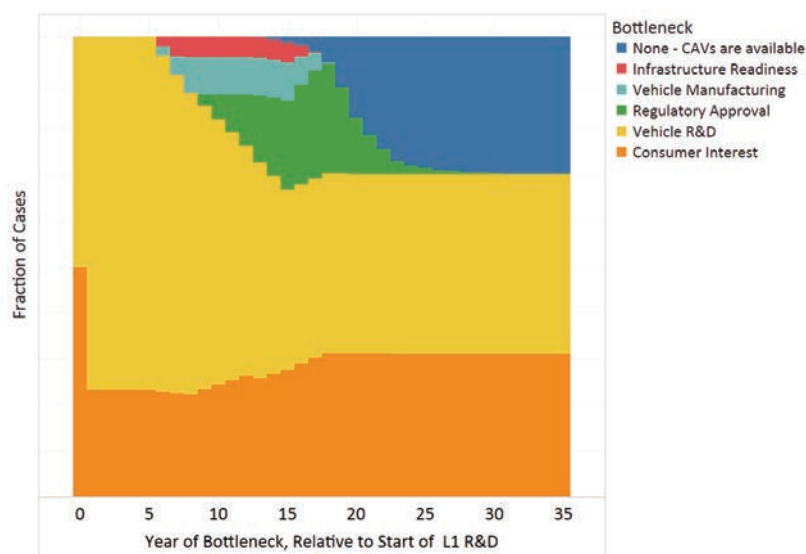


Figure II.4.1 Summary of the frequency of different bottlenecks to CAV adoption among the scenarios. Proportions of results in the figure should not be interpreted as probabilities of outcomes because input assumptions do not include probability distributions. (Source: NREL.)

The energy effects of CAVs vary significantly by scenario. Figure II.4.2 illustrates that the long-term energy outcomes of various CAV scenarios differ by half an order of magnitude. Because the computer experiment did not vary vehicle occupancy or deadhead miles and because the vehicle efficiency was assumed to be highest in L4 vehicles, intermediate in L1 vehicles, and lowest in L0 vehicles, lower energy use tends towards cases with higher predominance of L4 vehicles. Figure II.4.3 shows a regression tree that indicates consumer preference and variable costs are the primary influences on the choice of L4 over L1 and L0 concepts. Figure II.4.4 demonstrates the wider range of fuel-consumption outcomes and highlights that the more extreme outcomes are associated with higher L4 automated taxi adoption. Such results could facilitate screening to select conditions for further analysis. Similarly, Figure II.4.5 displays results from the energy sensitivity study in comparison to ranges of CAV assumptions from Stephens et al., potentially indicating screening criteria that could be applied to select regions of the parameter space of greatest interest for more detailed analysis.

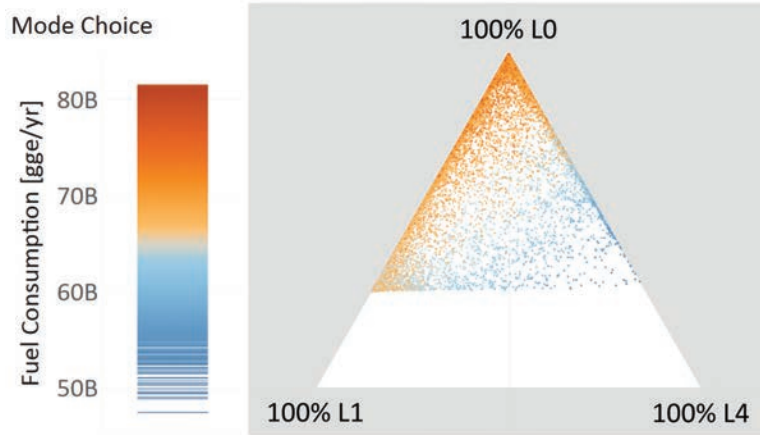


Figure II.4.2 Fuel-consumption outcomes for scenarios in the screening study. Each corner of the triangle represents a “pure” Level 0, Level 1, or Level 4 vehicle fleet and points in between those corners represent outcomes with mixes of those vehicle types. (Source: NREL.)

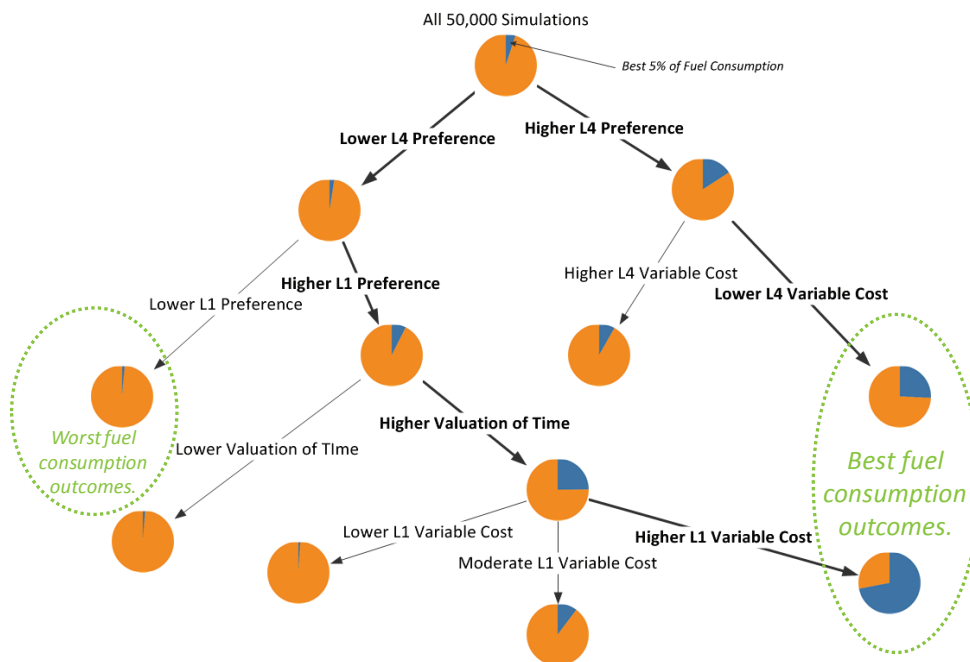


Figure II.4.3 Regression tree showing major influences on energy consumption. Each pie chart shows the fraction of results that lie in the best 5% of fuel consumption within simulations selected by the preceding branching criterion. (Source: NREL.)

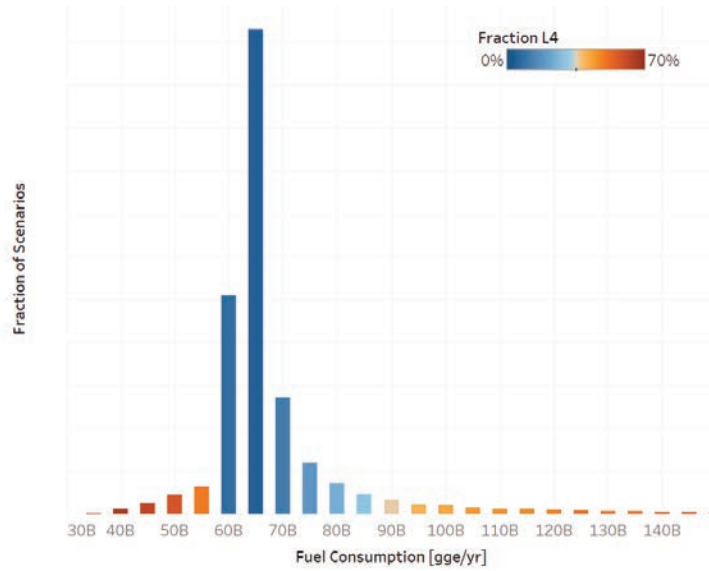


Figure II.4.4 Distribution of energy outcomes for scenarios, distinguished by the predominance of L4 CAVs in the scenarios. (Source: NREL.)

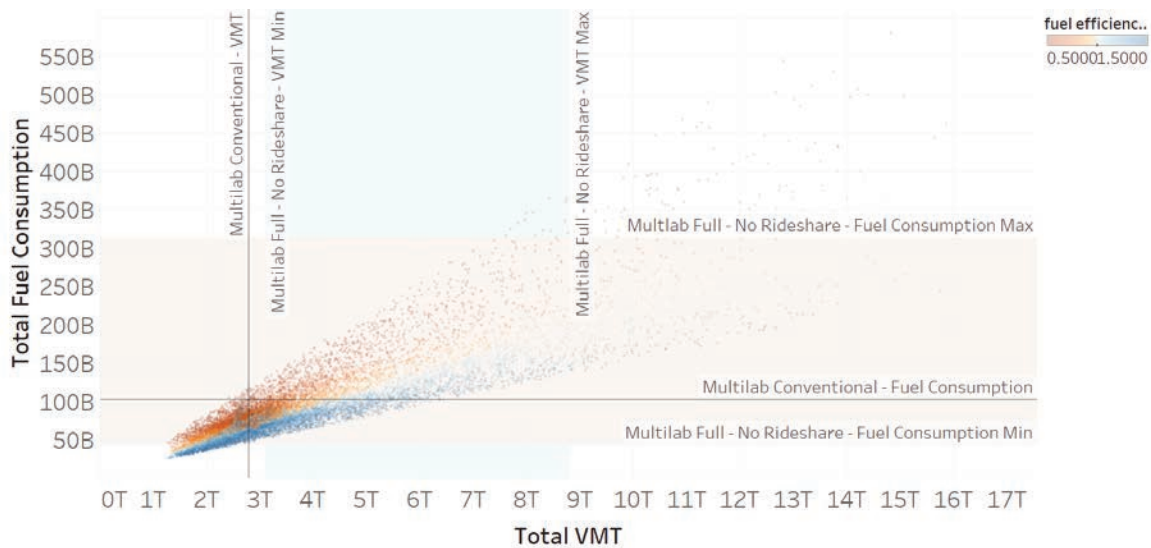


Figure II.4.5 Comparison of fuel consumption vs. total vehicle miles traveled (VMT) in energy sensitivity analysis (each point represents one of the simulations from the energy sensitivity study) relative to multi-lab study scenarios (lines and shaded ranges) as reported in Stephens et al.

A utility value for travelers in each cohort can be calculated as a function of cost, time, vehicle occupancy, and demand and can be averaged across cohorts to estimate a utility value for each simulation. Plots of the average utility value versus fuel consumption could provide a valuable comparison across scenarios. For example, using the preliminary results from the energy sensitivity study, Figure II.4.6 illustrates how scenarios with a lower L4 adoption have a larger range of utilities, but a smaller range of energy consumption, compare to scenarios with higher L4 adoption.

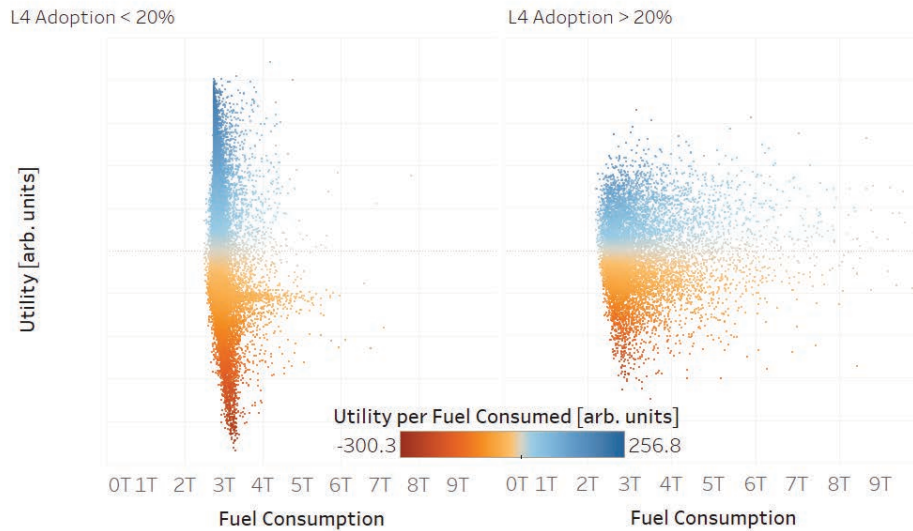


Figure II.4.6 A traveler's utility is calculated for each simulation as a function of capital and operating costs for travel, the time taken, vehicle occupancy, and demand for travel. Each point in the figure is the value of average utility of travelers versus fuel consumption in a single simulation. The left panel shows simulations with Level 4 adoption below 20%; the right panel shows those with Level 4 adoption above 20%. Travelers prefer higher utilities to lower ones.

Conclusions

Ongoing work on CAVs tipping-point dynamics has continued to demonstrate the 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. During FY18, we incorporated additional data and expanded sensitivity analyses. We analyzed CAV tipping-point dynamics in detail by generating hundreds of thousands of sensitivity simulations of CAV adoption scenarios. Future work will explore adoption differences among urban areas and analyze additional vehicle technologies and services, including commercial delivery services.

Key Publications

1. The results of this task were submitted for presentation at the Annual Meeting of the Transportation Research Board and publication in the *Transportation Research Record*. The submission, "Potential Energy Implications of Connected and Automated Vehicles: Exploring Key Leverage Points through Scenario Screening and Analysis" was accepted for presentation and the manuscript will be revised and resubmitted for consideration as a publication.

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2. Stephens, T. S., Gonder, J., Chen, Y., Lin, Z., Liu, C., & Gohlke, D. "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles," NREL Technical Report TP-5400-67216 (2016).

Acknowledgements

Jeff Gonder, NREL, serves as Co-Principal Investigator for this effort. Laura Vimmerstedt, NREL, supports this project as an energy analyst.

II.5 Multi-scale, multi-scenario assessment of system optimization opportunities due to vehicle connectivity and automation – (ORNL) [Task 2.1]

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Start Date: October 1, 2017	End Date: September 30, 2018	
Project Funding (FY18): \$364,000	DOE share: \$364,000	Non-DOE share: \$0

Project Introduction

Connectivity and automation provide opportunities for implementation of innovative and effective system-level monitoring and control. Coordination control systems for connected and automated vehicles (CAVs) operating in different traffic scenarios can potentially improve traffic efficiency, safety, and energy consumption. However, most of the current research in connectivity and automation is focused mainly on safety leaving still many open questions and uncertainty regarding the energy impacts of these new technologies. The uncertainties become even higher when the interaction between human drivers and vehicles with connectivity and automation capabilities is considered. In this context, further exploration of mobility gains and energy savings potential is needed. This project aims to investigate opportunities to optimize traffic systems through connectivity and automation and assess their performance under different scenarios. In particular, it explores the potential energy savings and efficiency improvements that can be achieved through coordination control systems for CAVs, contributing to the SMART Mobility program goal of yielding meaningful insights on how SMART technologies can improve Mobility Energy Productivity. It will also provide new insights regarding efficient coordination/control strategies that could offer energy and mobility improvements.

Objectives

Develop optimal vehicle coordination strategies to increase mobility energy efficiency and a simulation framework to verify their effectiveness in partial and full CAVs market penetration scenarios

- Apply the developed coordination strategies and assess their performance on traffic corridors
- Enhance accuracy of the fuel consumption models

Approach

The approach taken to accomplish the objectives of the project for this period of performance involved:

- Integration of enhanced fuel consumption models. A polynomial metamodel was calibrated using data obtained from higher fidelity models.
- Adaptation of the optimal coordination and simulation framework developed in the previous period of performance to traffic corridors

- Simulation-based assessment of the CAVs optimal coordination framework applied to traffic corridors considering different traffic scenarios
- Exploration of communication-related challenges Collaborations with the University of Delaware and the University of Tennessee Knoxville helped with the adaptation of the optimal coordination framework to an urban corridor and the ongoing exploration of communications-related challenges respectively. Recently, through collaboration with ANL, Autonomie models are being used for fuel consumption estimations.

Results

1. Enhanced fuel consumption models

A polynomial metamodel for estimation of fuel/energy consumption was calibrated based on simulation data from *Autonomie*. The polynomial model estimates fuel/power consumption as a function of speed and acceleration ($f = f_{cruise} + f_{accel}$), where $f_{cruise} = b_0 + b_1v + b_2v^2 + b_3v^3$ and $f_{accel} = a(c_0 + c_1v + c_2v^2)$, f_{cruise} and f_{accel} are the fuel consumption during cruising and acceleration phases, b_i and c_i are coefficients to be tuned, v is speed and a is acceleration.

Fuel consumption (or power), speed, acceleration and time data is used to calibrate the polynomial model, i.e., finding the coefficients values that will better fit the data for a specific vehicle. The coefficients are found by curve fitting using actual or simulated (from higher fidelity models) data. Once the model is calibrated, it will use speed and acceleration as inputs to estimate the fuel/power consumption (Figure II.5.1 left).

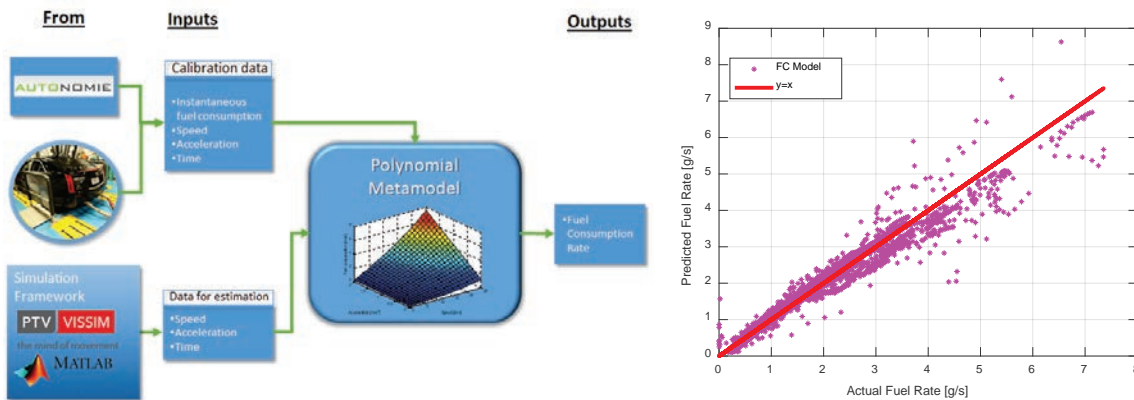


Figure II.5.1 Fuel/Power consumption estimation process (left), curve fitting for a medium duty vehicle (right)

Figure II.5.1 (right) illustrates the curve fitting for a medium duty vehicle where the coefficients b_i and c_i are $b_0 = 1.04 \times 10^{-4}$, $b_1 = 2.23 \times 10^{-5}$, $b_2 = -1.49 \times 10^{-6}$, $b_3 = 2.99 \times 10^{-8}$, $c_0 = 8.67 \times 10^{-5}$, $c_1 = 1.42 \times 10^{-4}$, $c_2 = -1.16 \times 10^{-6}$. The loss of accuracy of the calibrated model (with respect to Autonomie data) for three standard driving profiles, i.e., Federal Highway Driving Schedule (FHDS), Urban Dynamometer Driving Schedule (UDDS) and US06, is included in Table II.5.1.

Table II.5.1. Loss of accuracy for a medium duty vehicle

Loss of Accuracy [%]	FHDS	UDDS	US06
Medium duty vehicle	0.46	2.8	2.18

2. Optimal coordination on interconnected traffic scenarios

2.1. Full market penetration

2.1.1. Highway corridor

The effectiveness of the proposed optimal coordination framework was evaluated through microscopic traffic simulations using VISSIM software and compared to a baseline scenario in which all the vehicles are driven by human drivers. The simulation is performed for a highway corridor (corridor length 2.5 km) scenario with two on-ramp roads and one off-ramp road (Figure II.5.2) to analyze the effects of local coordination at merging on-

ramps. To represent the longitudinal driving behavior of humans in the baseline scenario, we used the psycho-physical driver behavior model developed by Wiedemann included in VISSIM (Wiedemann 99) and assumed that the desired speed is set to 50 km/h for control zone 1 and 60 km/h for control zone 2. We also considered homogeneous traffic. The traffic demand for the main and ramp road 1 was set to 1400 veh/h and 600 veh/h, and three different traffic demand scenarios were considered for the ramp road 2: 1) 1200 veh/h, 2) 1500 veh/h, and 3) 1800 veh/h. The exit rate of vehicles on the off-ramp road is set to 30 %. The simulation results are illustrated in Figure II.5.3.

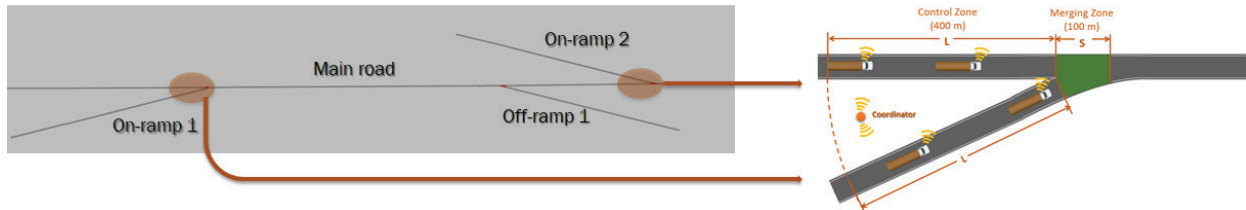


Figure II.5.2 Simulation scenario - highway corridor

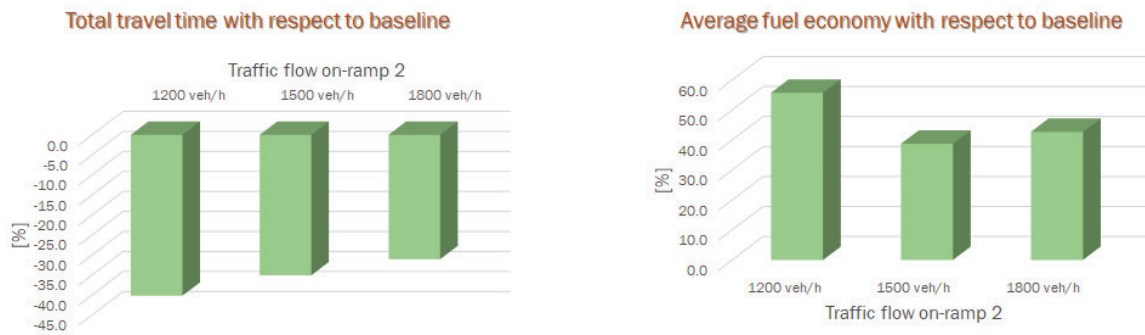


Figure II.5.3 Simulation results - highway corridor

By following the optimal control inputs, the vehicles traveling on the corridor follow smoother acceleration patterns which avoid the frequent stop-and-go driving commonly observed in baseline scenarios. This way the optimal coordination mitigates the traffic jam propagation with significant reduction of travel time and improved fuel economy with respect to the non-coordinated scenario as shown in Figure II.5.3.

2.1.2. Urban corridor

Using VISSIM, we define a study corridor (in MCity) that consists of a highway on-ramp, a speed reduction zone (SRZ), a roundabout, and an intersection (see Figure II.5.4).

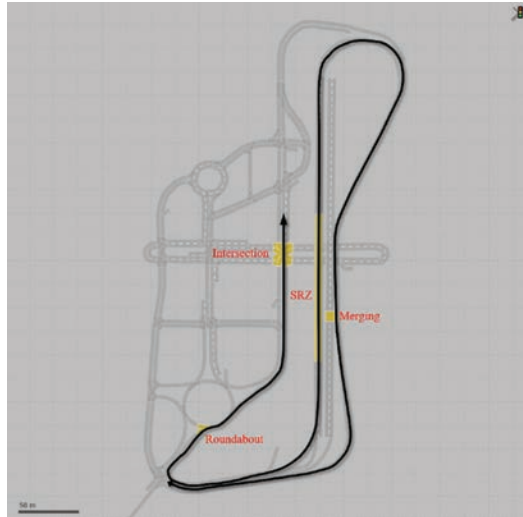


Figure II.5.4 Simulation scenario - urban corridor

Vehicles enter the network on the ramp, join the traffic on the highway with a desired speed of 25 m/s, and then enter the SRZ where the speed limit drops to 11 m/s. Exiting from the highway segment, the vehicles travel through the roundabout, where a desired speed of 13 m/s is in effect, until the end of the path (corridor length 1.26 km). To evaluate the network performance with the proposed control algorithm, we analyze two cases with different traffic demand levels. The case 1 represents the baseline scenario where all vehicles in the network are non-connected and non-automated vehicles. In this case, the Wiedemann car following model built in VISSIM is applied. 1.2 s time headway is adopted to estimate the minimum allowable following distance. The case 2 represents the optimal case (100% market penetration of CAVs), where all the vehicles follow the proposed optimal control algorithm. The proposed control framework is applied in this case to recommend optimal acceleration/deceleration for each CAV in the network. The same time headway as in case 1 is applied in the optimal control model. Table II.5.2 summarizes the traffic scenarios created (and evaluated for baseline and optimal cases).

Table II.5.2 Summary of traffic scenarios

Loss of Accuracy [%]	Corridor [veh/h]	Highway [veh/h]	Urban [veh/h]
Scenario 1	200	600	300
Scenario 2	300	1000	500
Scenario 3	400	1400	600

By eliminating vehicles' stop-and-go driving throughout the corridor, transient engine operation is minimized through the optimal control algorithm, leading to direct fuel consumption savings with respect to the baseline case as shown in Figure II.5.5.

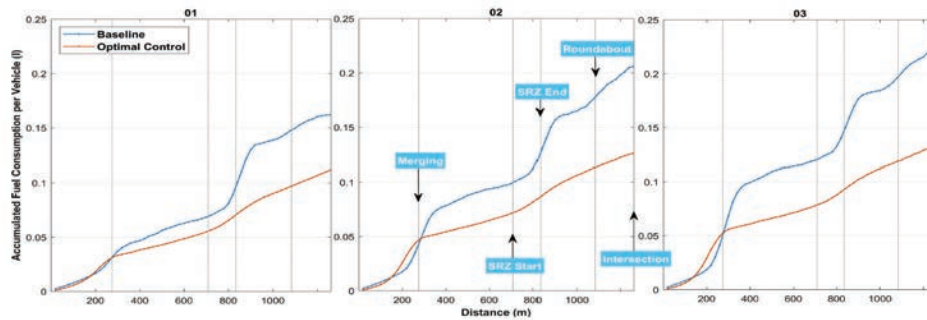


Figure II.5.5 Accumulated fuel consumption per vehicle along the corridor

We can observe a large difference in accumulated fuel consumption especially after the merging point. While CAVs are immediately preparing for the following conflict zones the human-driven vehicles are traveling with higher speed until they are aware of the downstream conflict zones. Also, CAVs are coordinated with each other to create enough gaps for merging and crossing the intersection, whereas human-driven vehicles need to stop for mainline vehicles and wait for green light signal to cross the intersection. As traffic demand increases, a large speed drop is unavoidable even in the optimal control cases. However, the optimal corridor control still yields substantial fuel economy improvement and travel time reduction as seen in Figure II.5.6.

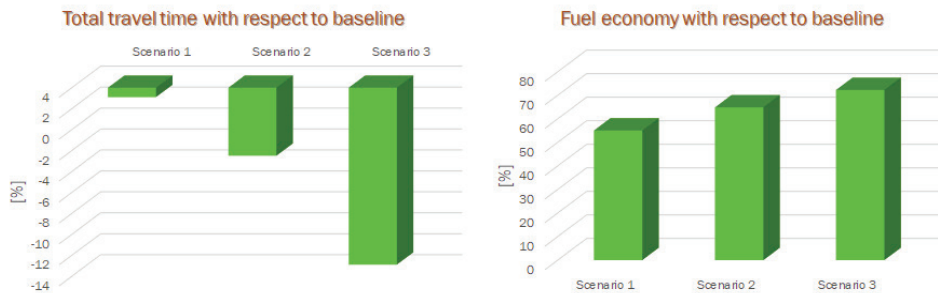
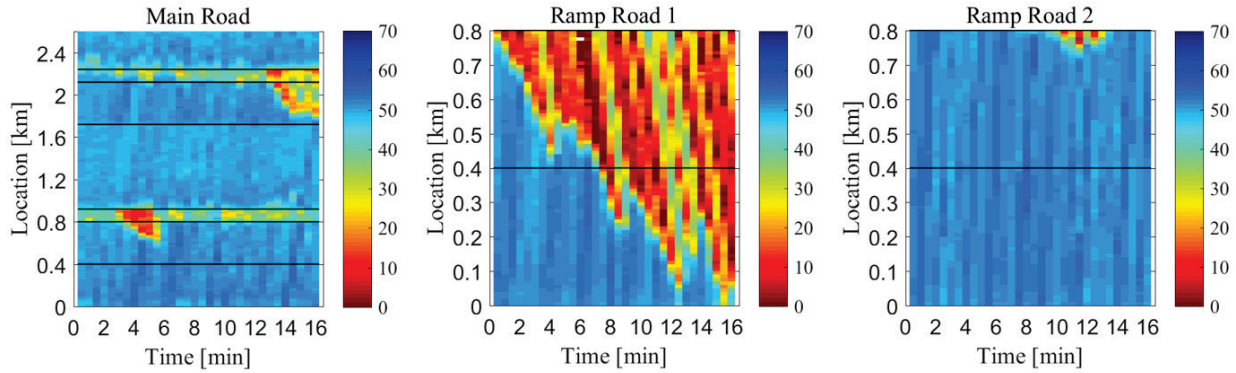


Figure II.5.6 Simulation results - urban corridor

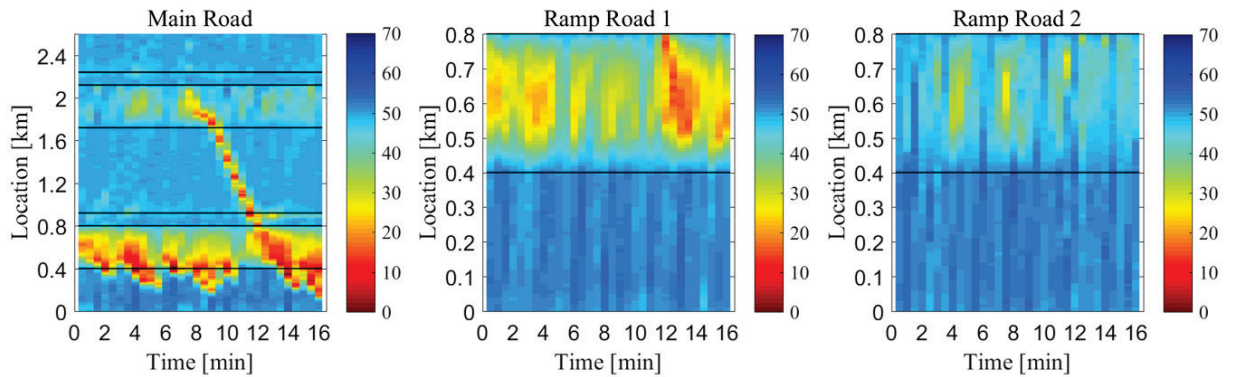
2.2. Partial market penetration

To evaluate the effectiveness of the proposed optimal coordination framework in a highway corridor and considering partial market penetration of CAVs and heterogeneous traffic (LDVs and HDVs), it is necessary to enforce a position constraint ($p_{i-1}(t) - p_i > \delta p_{safe}$) in the controller solution to avoid rear-end collisions which might occur as a result of inaccurate estimation of the human-driven (non-connected) vehicles behavior. We use the highway corridor illustrated in Figure II.5.2 and conducted simulations considering a fixed traffic demand for main and ramp roads $(Q_m, Q_{r,1}, Q_{r,2}) = (1200, 1000, 600)$. We also assumed a fixed ratio of light duty/heavy duty vehicles (90/10) and different penetration rates of optimally coordinated connected and automated light duty vehicles (LDCAVs). In simulations, one penetration rate of connected and automated heavy-duty vehicles (HDCAVs) is considered (100%), i.e., the total 10% of trucks in the traffic network are all assumed to be connected and automated. For the case of LDVs we assume 0% (baseline) and 60% penetration rates (due to space constraints, further results will be part of a future publication). Additionally, we consider the exit rate to the off-ramp road to be 30%.

The spatial-temporal distribution plots for mean speed are shown in Figure II.5.7. In the baseline case (Figure II.5.7 (a)) the main road vehicles reduce the speed to values below 30km/h near the two merging zones. The worst traffic condition is observed in ramp 1 where the vehicles perform stop-and-go driving that propagates upstream the ramp. This congestion is due to the vehicles located near the merging zone that are waiting for a safe gap to merge into the main road.



(a) Scenario 1: 0% PR HDCAVs, 0% PR LDCAVs



(b) Scenario 2: 100% PR HDCAVs, 60% PR LDCAVs

Figure II.5.7 Spatial-temporal distribution of mean speed plots of main and ramp roads (Black lines indicate the start and end of the control and/or merging zones)

In contrast, by introducing high penetrations of optimally coordinated LDCAVs, i.e., 60% (Figure II.5.7 (b)), the traffic flows smoother in the ramp 1 while some effects are observed on the main road and the ramp 2 where the average speed is slightly decreased, and the traffic density increased, particularly on the main road. Ongoing work is exploring the impacts of additional penetration rates both on traffic and fuel consumption.

Conclusions

Microscopic traffic simulations have been performed to test the performance of the developed optimal coordination controller. The effectiveness of the controller to improve fuel economy and reduce travel time on traffic corridors has been demonstrated under 100% penetration of CAVs considering different traffic conditions and a highway and an urban corridor.

The coordination framework has been adapted to operate safely in a scenario including mixed traffic, i.e., CAVs interacting with human drivers. In this partial penetration case, preliminary results reveal that the 60% penetration of CAVs can aid to mitigate the propagation of traffic bottlenecks at the expense of a slight speed reduction on the main road considering a hypothetical highway corridor with two on-ramps. Ongoing research is exploring the effects of additional penetration rates on traffic conditions and fuel efficiency considering

heterogeneous traffic (different vehicles classes/powertrains). We are also exploring the impacts of optimal coordination applied to real-world traffic scenarios and the effects of communication instabilities in the overall performance of the control.

Key Publications

1. J. Rios-Torres and A. Malikopoulos, "Impact of Partial Penetrations of Connected and Automated Vehicles on Fuel Consumption and Traffic Flow," in *IEEE Transactions on Intelligent Vehicles*. doi: 10.1109/TIV.2018.2873899 (*in press*)
2. Han, J., Rios-Torres, J., Vahidi, A., Sciarretta, A., "Impact of model simplification on optimal control of combustion engine and electric vehicles considering control input constraints" 2018 IEEE Vehicle Power and Propulsion Conference (*forthcoming*)
3. Zhao, L., Malikopoulos, A.A., Rios-Torres, J., "Optimal Control of Connected and Automated Vehicles at Roundabouts: An Investigation in a Mixed-Traffic Environment," *Proceedings of the 15th IFAC Symposium on Control in Transportation Systems (CTS 2018)*, pp. 73–78, 2018.
4. Lihui Zhao, Andreas Malikopoulos and Jackeline Rios-Torres. "Optimal Control of Connected and Automated Vehicles at Roundabouts" 97th Annual Meeting Transportation Research Board, 2018
5. J. Rios-Torres and A. A. Malikopoulos, "Impact of connected and automated vehicles on traffic flow," 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, 2017, pp. 1-6. doi: 10.1109/ITSC.2017.8317654
6. 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*, 93, 244–256, 2018
7. A. A. Malikopoulos, S. Hong, B. B. Park, J. Lee and S. Ryu, "Optimal Control for Speed Harmonization of Automated Vehicles," in *IEEE Transactions on Intelligent Transportation Systems*. doi: 10.1109/TITS.2018.2865561

Acknowledgements

We acknowledge the valuable contributions of Jihun Han and Andreas Malikopoulos, the insightful comments and feedback provided by Paul Leiby from Oak Ridge National Laboratory and the continued support of Eric Rask (CAVs Pillar lead).

We thank the Systems Modeling and Control Group from Argonne National Laboratory for providing higher fidelity models for fuel consumption estimation.

II.6 Multi-Scale, multi-scenario assessment of system optimization opportunities due to vehicle connectivity and automation (ANL) [Task 7A.2.1.1]

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Start Date: October 1, 2016	End Date: September 30, 2019	
Project Funding (FY18): \$660,000	DOE share: \$660,000	Non-DOE share: \$0

Project Introduction

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

Automation and connectivity also can be used for eco-driving—in which energy efficiency is another objective of the vehicle dynamics control—without compromising drivability and travel time. In parallel, vehicles feature an ever-broader range of advanced powertrain technologies, from hybridization to transmissions with a high number of gears, designed to improve the overall vehicle efficiency. It is uncertain how combining powertrain and Connected and automated vehicle (CAV) technologies will impact energy efficiency improvements: will one cancel the benefit of the other, or will they add up? Will there be synergies from 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 the impacts be in the real world, not just in the best-case scenarios?

This project aims to tackle these challenging questions by designing eco-driving and energy-management strategies for vehicles with advanced powertrain technologies, and by 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: simulation of powertrain and driving dynamics for CAVs

Vehicle-level simulations for estimating energy consumption typically model driving with a drive cycle (i.e., predefined speed as a function of time). This approach is not suitable for CAVs, where the vehicle itself dynamically decides its own speed based on its environment. As a result, in previous years we initiated in the development of RoadRunner: a framework that can simulate multiple vehicles with full powertrain models and the interactions between vehicles and their environment. RoadRunner uses powertrain models from Autonomie, Argonne's established vehicle energy-consumption simulator, but adds new capabilities such as multi-vehicle simulation, models of the road, causal models of human driving, V2X communications, and sensors. Figure II.6.1 illustrates the steps in a typical RoadRunner use case. The user first defines a scenario: the route, the number of vehicles, the type of vehicles, and the type of CAV technology for each vehicle. RoadRunner then automatically builds the Simulink diagram, runs the simulation, and post-processes the results for the user to analyze.

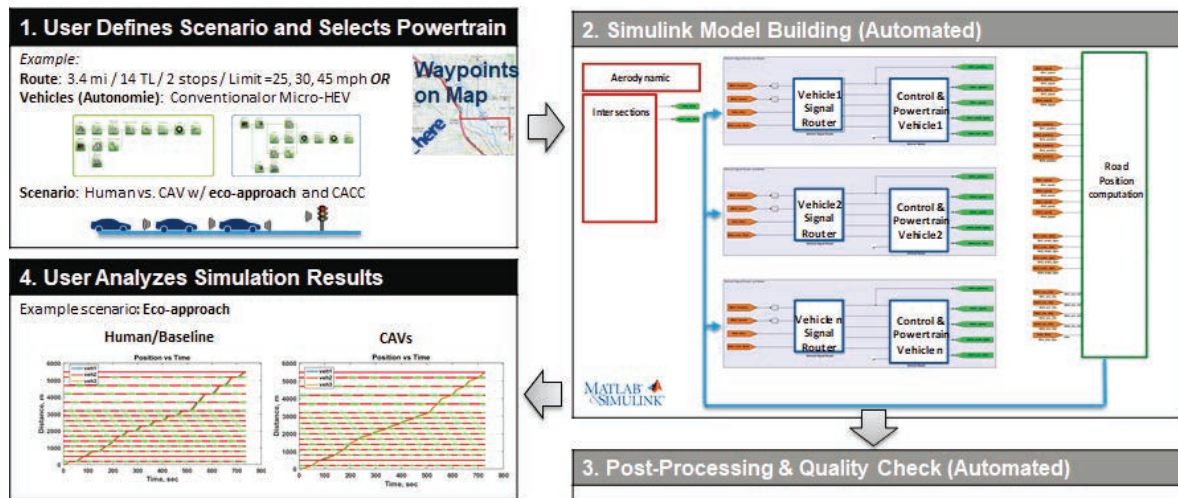


Figure II.6.1 RoadRunner workflow to simulate a CAV scenario

Eco-driving for CAV

Eco-driving consists of adjusting vehicle speed to minimize energy consumption, for example coasting to a red light. Although some experienced human drivers practice eco-driving, it can be more systematically applied in CAVs, thanks to the active velocity control by onboard computers and environmental awareness from sensors and V2X. Our research seeks practical and implementable control strategies CAVs can use to drive in an energy-efficient fashion, and to evaluate their real-world energy impact.

We will eventually use RoadRunner to demonstrate the eco-driving controllers developed as part of this project. As a result, these controllers will have to interact with advanced models of the powertrain, including transient dynamics, and only receive information about surrounding environment that can be realistically obtained in a real-world situation. In other words, such controllers will address some of the challenges of implementation typically not addressed in more theoretical approaches. One key requirement for the controller is for it to adapt to a changing environment and to the response of the vehicle itself, accounting for the imperfection of models assumed during the optimization and the uncertainty of the environment.

Model-Predictive Control (MPC) is a technique that accomplishes this requirement, so the first focus in this project is to implement and demonstrate an eco-driving controller with embedded MPC. MPC uses the concept of receding horizon: at each time step, MPC computes the optimal command and state trajectories over an

entire finite horizon (e.g., the next 20 seconds), but only applies the first step of the optimization. In the following time step, the horizon window moves one step further and the optimization is performed again. As a result, MPC performs the optimization at each time step with the most recent information about the state of the system, which creates a feedback loop that is critical to the stability of the system. MPC is a well-established approach, and is particularly well suited for linear and quadratic systems; in such cases, the optimization method applied at each time step is Quadratic Programming (QP), which is relatively fast and simple to implement. However, the linearity condition limits the number of control variables QP can optimize, and therefore leads to suboptimal results.

Therefore, the other focus of this project is to develop optimization algorithms for advanced powertrains and that can be incorporated in the MPC framework. We can achieve this by applying optimal control theory to the eco-driving problem: given a horizon, constraint, and initial and final conditions, which control variable sequence results in the lowest energy consumption cost over the horizon? The optimization algorithm takes into account all the control variables in the optimization, so that velocity and powertrain are optimized simultaneously. This is critical to ensure maximum energy savings from vehicles with both advanced powertrain technologies (e.g., hybrids) and CAV capability.

Results

Powertrain operation impact of eco-approach algorithms

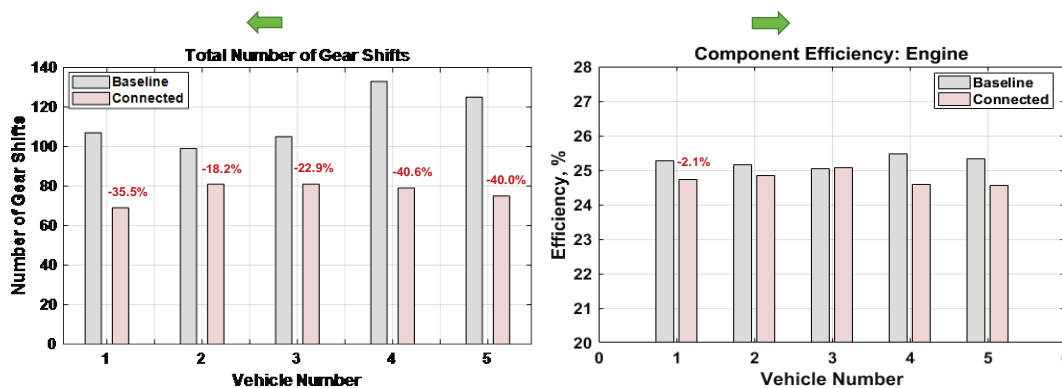


Figure II.6.2 Eco-approach impacts on the energy benefits of components

To evaluate the impact of connectivity on powertrain operation, we developed an eco-approach scenario that we then applied to five conventional engine-powered vehicles. The eco-approach algorithm, inspired by literature, features a speed-only control logic that minimizes average tractive energy consumption and avoids stopping at red lights based on information about incoming signal phase and timing. We ran simulations for selected routes in the Chicago area, and fuel savings ranged from 5 to 9%. The resulting operating points are shown in Figure II.6.2. We demonstrated a 30 to 40% reduction in the number of shifts for each gear, especially for high gears. The reduction of demand for acceleration also leads to higher engine operation at low loads in the eco-signal examples, and therefore to lower average engine efficiency.

Model validation of truck platooning in RoadRunner

We implemented in RoadRunner control algorithms inspired by literature for the intelligent driver model (IDM), adaptive cruise control (ACC), and cooperative ACC (or CACC). These models allow simulations of close-driving platooning scenarios. In a platoon, vehicles have reduced drag coefficients as a function of both inter-vehicle spacing and the number of vehicles. The aero drag reduction coefficients are integrated into RoadRunner for short-gap driving (wind tunnel data from Lawrence Livermore National Laboratory). We validated the model of a three-truck platoon in RoadRunner based on test data provided by Lawrence Berkeley Laboratory. RoadRunner builds the Simulink diagram of the scenario, including information flows between truck vehicle models. After the simulation, the results showed that discrepancies in average inter-vehicle gap

were within 4% compared to test data, while many of the operational signals, including fuel consumption, were well matched. Key highlights are shown in Figure II.6.3.

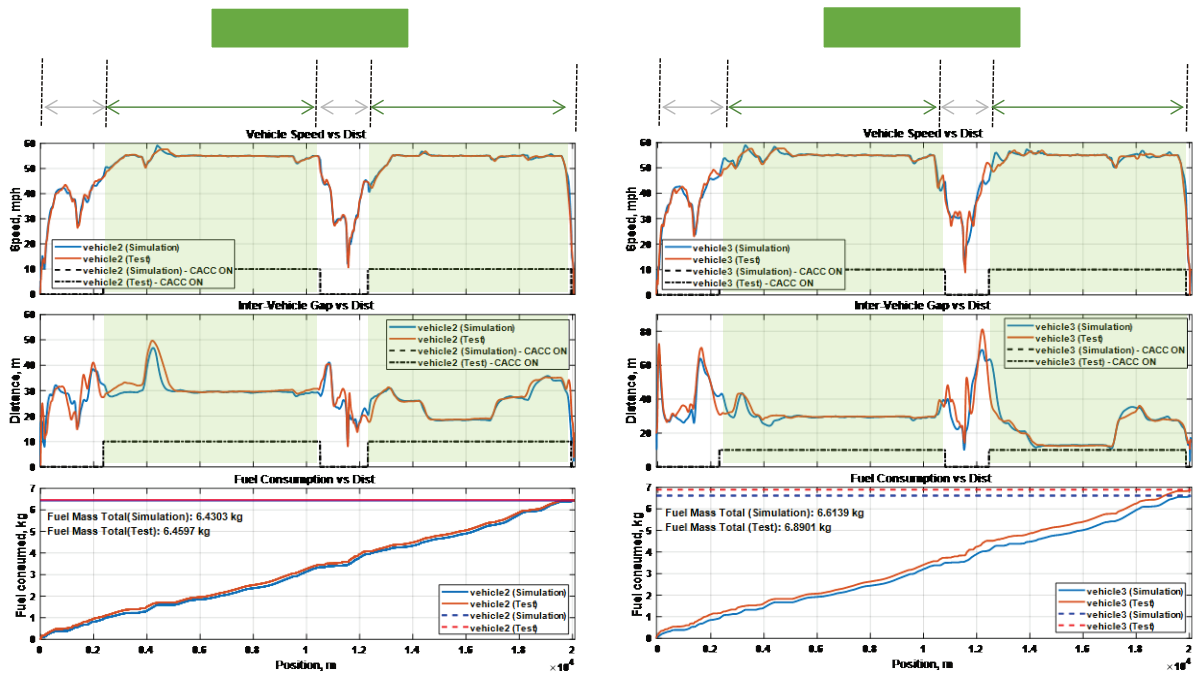


Figure II.6.3 CAV model validation on platooning scenario for middle (veh2, left) and trailing (veh3, right) vehicle

RoadRunner core developments

We have improved RoadRunner to better support eco-driving studies and accelerate public release. A better integration with Autonomie allows us to use plant models from vehicles defined in Autonomie, and the scenario definition is overall easier for the user. The road model can now be initialized from real-world routes as defined by their waypoints, thanks to the automated extraction of route attributes (position of traffic lights, grade, speed limits, etc.) from HERE Maps API. Finally, internal changes to the model organization of each simulated vehicle allow the simulation of a more vehicle supervisory control paradigms.

Real-world implementable eco-driving control with MPC

This year, we implemented the first controller in RoadRunner that optimizes both vehicle speed and powertrain operations. This control, based on the MPC framework and using QP for optimization, computes the optimal engine torque of a conventional engine-powered midsize vehicle with a 6-speed automatic transmission during a cruise control scenario. Gear shifting follows a default rule-based control strategy. We set the horizon for MPC to 500 m, and discretized the distance in 25-m steps. We evaluated the controller over three artificially generated short routes (7 km each) and two real-world routes (using HERE data), and compared these to a baseline human driver model that simply tries to follow the speed limits. The controller with MPC-QP yielded 3.2 to 6.8% better fuel economy, at the expense of longer travel time, as shown in Table II.6.1.

Table II.6.1 Comparison of fuel economy and travel time by controllers

Type of Driving	Fuel Economy/Travel Time				
	Artificial short cycle 1 (flat)	Artificial short cycle 2 (up-down)	Artificial short cycle 3 (down-up)	Real world 1 (Argonne to Chicago, 24 mi)	Real world 2 (Denver to Silverthorne, 54 mi)
Human driver	37.1 mpg/330 s	36.7 mpg/332 s	37.4 mpg/332 s	41.0 mpg/1443 s	28.9 mpg/3129 s
MPC-QP	38.7 mpg/342 s	39.1 mpg/350 s	39.6 mpg/341 s	42.8 mpg/1522 s	29.8 mpg/3274 s
Difference	4.3%/3.6%	6.8%/5.4%	6.0%/2.7%	4.6%/5.5%	3.2%/4.6%

The MPC-QP controller achieved better fuel economy thanks to smoother acceleration and deceleration at speed limit changes, optimal cruising speed, and grade anticipation. Better results could be achieved by adding more control variables to the optimization, but this would require solvers other than QP, which cannot handle the increased complexity; the following section details such alternatives.

Optimal control algorithms applied to CAV eco-driving

Optimal control theory is a method that is well suited for complex powertrain and speed co-optimization for eco-driving. We enhanced the optimal eco-cruise control algorithm developed in the first year of this project to take real-world route information as an input by processing the map data into segments with piecewise constant grades and speed limits [1], [3]. Case studies show up to 8% fuel saving potential for conventional vehicles, and 1.2% energy savings for electric vehicles. In these studies, the eco-cruise control relies on the assumption that optimal speed at steady state is constant—a simplifying assumption that allows analytical solutions to the control problem. However, we demonstrated that with a different formulation, optimal control theory leads to a periodic solution (i.e., where vehicle speed periodically oscillates) that alternates between acceleration and coasting. Up to 4% energy savings can be achieved, without detrimental impacts on driving comfort.

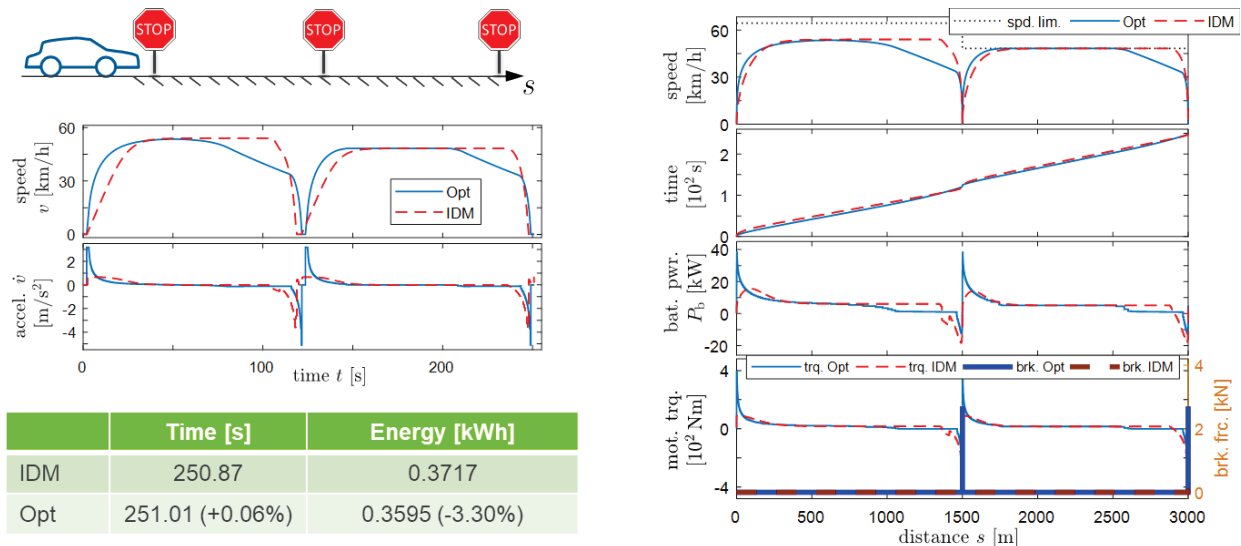


Figure II.6.4 Electric vehicle travel between stops

We also expanded the optimal control algorithm to car-following and intersection approach problems, which follow the same formulation as for eco-cruise control, but are subject to different types of constraints. Stop signs are point-constraints of speed (zero) in reference to distance. Figure II.6.4 shows the optimal control and

speed profiles (Opt) for an electric vehicle travelling between three stop signs with two speed limits, compared to the trajectories of human driving (modeled by the Intelligent Driver Model, IDM).

Car-following adds time-variant position constraints to the existing problem formulation. Unlike the other constraints, the occurrences of boundedness are ambiguous in terms of position. Our proposed algorithm uses iterative trial and error to recursively adjust the parameters in the optimization. This eventually eliminates all the constraint violations [3].

Conclusions

- We continued the development of RoadRunner to better enable eco-driving research.
- We analyzed the impact of connected and automated driving on powertrain operations: 5 to 9% fuel savings and a 30 to 40% reduction in shifting in an eco-approach scenario.
- We validated a model of a three-truck platoon in RoadRunner; the average inter-vehicle gap in the simulation was within 4% of the test data.
- We implemented an eco-cruise-control algorithm in RoadRunner that features model-predictive control and quadratic programming, and that creates 3 to 7% fuel savings for a conventional car.
- We improved the eco-cruise algorithm that optimizes speed and powertrain for vehicles with multiple degrees of freedom (e.g., hybrids) to work on real-world grades. Case studies show up to 8% fuel saving potential for conventional vehicles, and 1.2% energy saving for electric vehicles.
- We expanded the optimization algorithm to cover car following and intersection approaches.
- Future work will focus on further improvements and validation of the models in RoadRunner, and the evaluation of real-world implementable eco-driving strategies for advanced powertrain vehicles.

Key Publications

1. Daliang Shen, Dominik Karbowski, and Aymeric Rousseau, “Fuel Efficient Speed Optimization for Real-World Highway Cruising,” SAE Technical Paper 2018-01-0589, 2018, <https://doi.org/10.4271/2018-01-0589>.
2. Namdo Kim, Dominik Karbowski, Aymeric Rousseau, “A Modeling Framework for Connectivity and Automation Co-simulation,” SAE Technical Paper 2018-01-0607, 2018, <https://doi.org/10.4271/2018-01-0607>.
3. Daliang Shen, Dominik Karbowski, and Aymeric Rousseau, “Highway Eco-Driving of an Electric Vehicle Based on Minimum Principle,” 2018 IEEE Vehicle Power and Propulsion Conference August 27–30, 2018, Chicago, Illinois, USA.
4. Daliang Shen, Dominik Karbowski, and Aymeric Rousseau, “Fuel-Optimal Periodic Control of Passenger Cars in Cruise-Control Based on Pontryagin’s Minimum Principle,” 5th IFAC Conference on Engine and Powertrain Control, Simulation and Modeling, September 20–22, 2018, Changchun, China.
5. Namdo Kim, Dominik Karbowski, Jongryeol Jeong, and Aymeric Rousseau, “Simulation of Heavy-Duty Vehicles in Platooning Scenarios,” the 21st IEEE International Conference on Intelligent Transportation Systems, November 4–7, 2018, Maui, Hawaii, USA.

Acknowledgements

We would like to thank Kambiz Salari (Lawrence Livermore National Laboratory) for providing aerodynamic drag reduction coefficients for platooning trucks, calculated from wind tunnel testing. We are also grateful to Xiao-Yun Lu for providing the platooning test data used for validation.

II.7 Truck CACC operation at signalized intersections (LBNL) [Task 7A.3.1: Part I]

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Start Date: October 1, 2017	End Date: September 30, 2018	
Project Funding (FY18): \$269,000	DOE share: \$269,000	Non-DOE share: \$0

Project Introduction

Work accomplished under this task includes two aspects related to CACC (Cooperative Adaptive Cruise Control) trucks: (A) Control Performance Analysis Based on Test Track Data; and (B) CACC truck and real-time simulation in the loop for intersection operation to evaluate energy consumption. Therefore, in the following report, each section contains two parts accordingly labeled with (A) and (B) respectively.

Objectives

Control Performance Analysis Based on Test Track Data

The extensive fuel consumption test conducted at Transport Canada Test Track in Blainville, Canada covers variety of maneuvers including:

- Separation Distance/Time: 4 m (13 ft) to 87 m (285 ft), equivalent to 0.14 s to 3.0 s at 65 mph (105 km/h).
- Truck and trailer configuration: standard trailer with aerodynamic treatment (side-skirts + boat-tail).
- Vehicle speed: 89 km/h (55 mph) and mostly 105 km/h (65 mph).
- Vehicle weight (tractor + trailer): 14,000 kg (31,000 lbs) and 29,400 kg (65,000 lbs)
- One tractor towing two loaded trailers, operating as a Long Combination Vehicle
- 2-truck or 3-truck CACC strings following a manually driven SUV
- Cut-in and cut-out by an SUV between truck 1 & 2, and between truck 2 & 3
- Speed variation between 55 and 65 mph

The objectives of this part of work is to reuse the available test data for control performance analysis. The outcome of the analysis could be used for three purposes in the future: (a) to understand the statistical behavior of the three CACC system in different maneuvers; and (b) to find out the limit of the CACC system which could have implications for next stage field operational test with public traffic;

and (c) for possible performance improvement in the future if there is any chance to refine the controller. This part of work was partially funded by EEMS.

CACC Truck and Real-time Simulation In-the-Loop for Intersection Operation

The objectives for this part of work are: Develop a HIL (Hardware-in-the-Loop) simulation environment at Richmond Field Station (RFS) experimental intersection by: (1) generating an intersection traffic model in Aimsun based on real-time traffic data we already have; (2) developing and integrating Active Intersection Traffic Signal Control with Aimsun simulation incorporating CAVs; (3) integrating through I2V & V2I communication the experimental CACC-trucks with the intersection traffic signal controller; and (4) extensive field test of the CACC truck in this environment for the evaluation of any fuel saving benefit for such cooperative operation of CACC trucks and an intersection.

Approach

A. Control Performance Analysis Based on Test Track Data

- i. Field test data preparation of three CACC trucks for different scenarios, which was obtained during the test on Transport Canada Test Track in Blainville near Montreal of Canada in August 2017;
- ii. Quantitative analysis of the closed-track test data for most important scenarios with speed and distance tracking errors as the performance measures. The statistics used are:
- iii. Speed Error [m/s]: the speed tracking error of each truck in meters per second; it is defined as the difference between the reference speed and the measured truck speed, which is quantified as: root mean square (RMS) error and maximum value.
- iv. Distance Error [m]; the distance tracking error of each truck in meters; it is defined as the difference between the reference distance and the measured front gap in meters, which is quantified as: root mean square (RMS) error and maximum value.

B. CACC Truck and Real-time Simulation In-the-Loop for Intersection Operation: The Concept of Operation is described below as shown in Figure I.6.1: 3 trucks using low speed CACC; the first truck is to be driven manually and the three trucks are connected with DSRC (Dedicated Short Range Communication); the live trucks, real-time simulation, and Active Traffic Signal Control will be integrated in the following sense

- i. Using the PATH research intersection at RFS as the test site, which will be modeled in the microscopic traffic simulation package Aimsun; the model will be calibrated using field collected traffic data; the demand for other movements will also be generated from field collected traffic data; while the CACC truck string will be added or imbedded in one major movement, which will be reflected in real time in the microscopic traffic simulation.
- ii. (a simplified optimal control (Model Predictive Control) or other appropriate control approach will be used to generate: (1) traffic signal control, and (2) desired (advisory) speed for CAVs for minimizing the total travel time directly (or, fuel consumption indirectly) by integrating the intersection signal operation with CACC truck operation; the overall simulated virtual traffic will be used for traffic signal control and the corresponding fuel consumption; the green distribution (control parameters) thus generated will be used for practical traffic signal control of the intersection and the desired speed of the corresponding movement will be used as the set-speed of the real trucks for CACC operation through the intersection.

The following figure shows the main components to be included in the system:

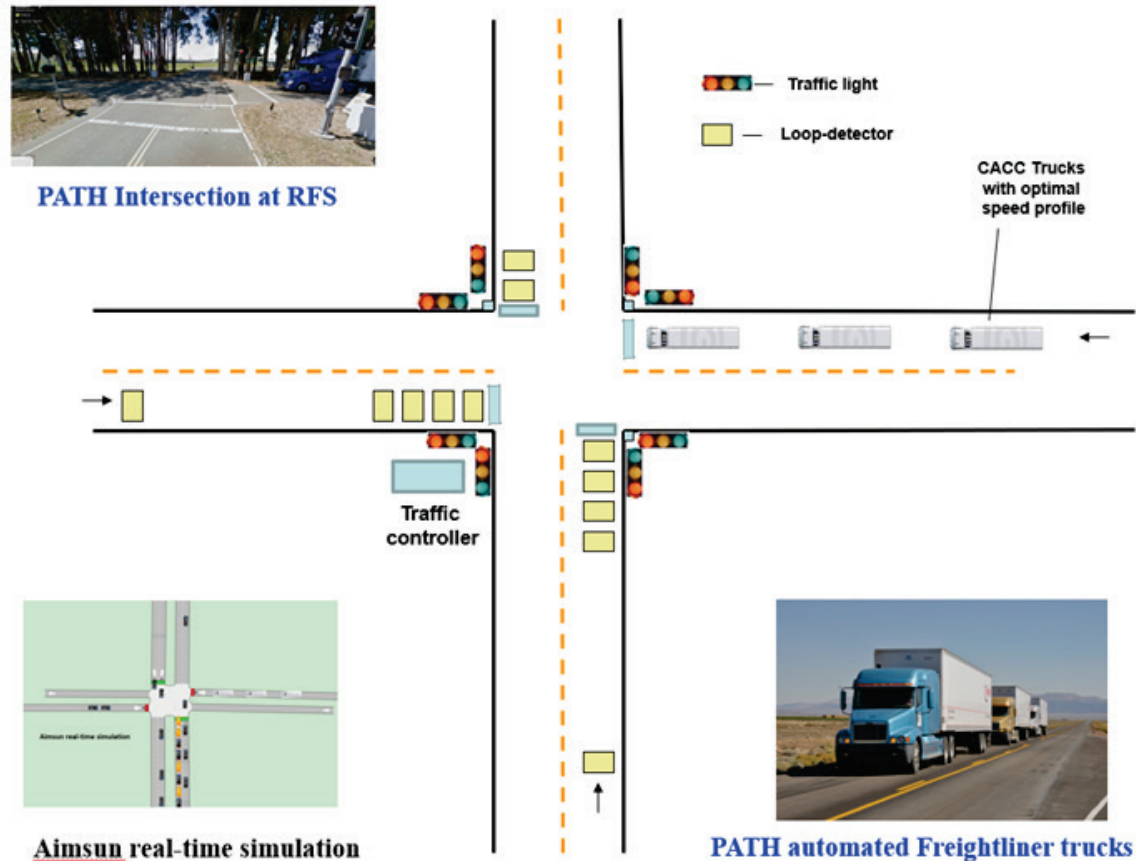


Figure II.7.1 The Concept of Operation of Integrated CACC Trucks, real-time microscopic traffic simulation in Aimsun, and Active Traffic Signal Control.

Results

Control Performance Analysis Based on Test Track Data

Transport Canada Motor Vehicle Test Track data included fundamental maneuvers such as constant speed following at different time gaps, cut-in and cut-out between trucks 1 and 2, and between trucks 2 and 3, long combination (one tractor towing two full-size trailers), speed variations between 55 mph ~ 65 mph etc. Since each run of a scenario on the track was for 64 miles, and each scenario had three successful runs, it makes sense to use such test data for statistical analysis of the control performance with respect to those scenarios. The following are the results:

Constant Time Gap Following

Since the vehicle speed is constant at 65 mph, for a given constant time gap, the clearance distance will not change. Therefore, the test scenario is similar to platooning (or constant clearance distance following). This subsection focuses on the test data analysis for performance of three-truck CACC following at distances: 18 m, 6 m and 4 m.

Table II.7.1 shows the speed and distance tracking errors for three T-Gaps (D-Gaps): 0.6 s (18 m), 0.21 s (6 m), and 0.14 s (4 m) respectively. Each scenario has been tested on the track for 16 laps, which is 64 miles and each condition has been repeated three times.

Table II.7.1 Root Mean Square and Maximum of tracking errors

Maneuver	D_Gap [m]	Vehicle Position	Speed Error [m/s]		Distance Error [m]	
			RMS	Max	RMS	Max
ACC	6m	1	0.05	0.55	0.19	0.45
CACC	6m	2	0.08	1.00	0.17	0.54
CACC	6m	3	0.09	1.01	0.25	0.64
ACC	4m	1	0.06	0.70	0.21	2.09
CACC	4m	2	0.08	0.84	0.18	1.08
CACC	4m	3	0.10	0.76	0.28	1.41
ACC	18m	1	0.05	0.53	0.29	0.53
CACC	18m	2	0.08	1.11	0.19	0.84
CACC	18m	3	0.09	0.97	0.23	1.19

It can be observed from Table II.7.1 that the maximum distance following error for truck 3 is about 1.4 m, which causes concern for a 4 m distance following. To investigate the cause of such significant distance error with respect to the desired short following distance, driving modes and distance tracking errors of the three trucks have been analyzed. Two causes have been identified that caused the large distance tracking error:

- Transition from manual to automatic mode at the beginning of the run, which is the case for the 18 m and 6 m following cases respectively
- Driver accidentally switched off the automatic control

It can be observed from Table II.7.1 that CACC tracking errors are generally larger than ACC tracking errors, which seem unreasonable. In fact, since the CACC following scenarios were tested without any vehicle in front of the lead truck, the leader was actually under CC (Cruise Control) mode. In this mode, the reference trajectory is internally planned for smooth acceleration and deceleration. This is why it has less tracking error in CC mode than in CACC mode.

Cut-in and Cut-Out between Truck 1 & 2 on Test Track

When the cut-in maneuver was between truck 1 and truck 2, truck 1 (in CC mode) speed and distance tracking would not be affected, which is therefore ignored. The cut-in performance is similar for all the 16 laps (each lap has two cut-in maneuvers on the two straight track sections). More detailed data analysis showed the following behaviors: front target distance sudden drop (cut-in happened) → the subject truck (truck 2) speed drop → speed and following distance transitioned to the desired values → front target distance suddenly increased (when cut-out happened) → truck 2 speed increasing to close the gap until the desired distance gap was reached → both speed and distance tracking resumed to steady-state tracking. It is noted that the distance tracking error is about 2 m, which is much smaller than the actual distance changes during a vehicle cut-in maneuver. This is due to the reference distance trajectory planning while taking into account the characteristics of the cut-in maneuver. Otherwise, the distance tracking error would be significantly larger, which would cause large speed tracking errors. As a result, it would cause spikes in feedback control action and truck 2 would jerk significantly.

Since the cut-in happened between truck 1 and truck 2, the following behavior of truck 3 was directly affected by the speed changes of truck 2 and therefore indirectly affected by the cut-in vehicle. As a result, the speed

tracking errors are smaller than those of truck 2; and the distance tracking errors are also smaller on average. However, the speed and distance tracking error changing logics are similar to that of truck 2.

Table II.7.2 lists the speed and distance tracking errors of the three trucks. It can be observed that the maximum distance tracking error is nearly 2.5 m, even with trajectory planning for both desired speed and desired distance. This was due to the delay in driveline response caused by large truck mass and inertia. Practical ride quality of the subject truck during the cut-in maneuver still showed smoothness in performance, which is desirable.

Similar observations and conclusions can be made for the cut-in maneuver between trucks 2 and 3. In this case, trucks 1 and 2 would not be affected by the cut-in vehicle with the current control configuration. Truck 3 during the cut-in and cut-out should behave similarly to truck 2 in the previous maneuver, i.e., cut-in between trucks 1 and 2.

Table II.7.2 also shows the speed and distance tracking errors for cut-in maneuvers between trucks 2 and 3. It is noted that the maximum distance tracking error is 2.5 m for truck 3, which implies the latency of response for the third truck in the CACC string. It also shows that the practical string stability that could be achieved is ultimately bounded instead of asymptotic as designed in [1].

Table II.7.2 Cut-in Maneuvers: Root Mean Square and Maximum of tracking errors

Maneuver	D_Gap [m]	Vehicle Position	Speed Error [m/s]		Distance Error [m]	
			RMS	Max	RMS	Max
Cut in between 1 & 2	35	1	0.05	0.54	0.30	0.55
Cut in between 1 & 2	35	2	0.30	1.81	0.37	2.50
Cut in between 1 & 2	35	3	0.20	1.34	0.48	2.50
Cut in between 2 & 3	35	1	0.05	0.58	0.30	0.60
Cut in between 2 & 3	35	2	0.09	1.03	0.22	0.82
Cut in between 2 & 3	35	3	0.30	1.84	0.37	2.50

Three Truck CACC with Speed Variations

Response to speed variations of the first truck is the test case for *string stability* for any multi-vehicle following strategy including platooning and CACC from a control viewpoint. The reason is that the overall system delays and control responses will be reflected in the speed variation scenarios. Admittedly, the response also depends on the reference trajectory planning of each truck and the information that is used from the front truck, particularly, the maximum acceleration and deceleration. The effect of maximum deceleration on the feedback control would not heavily depend on the current speed of the truck since the total braking torque of the truck would not change significantly with speed. The acceleration capability of a fully loaded truck is rather limited as truck speed increases. From a control point of view, the reachable set of the engine torque control in the high-speed range is small. However, for commercial trucks with engine braking, higher vehicle speeds would correspond to higher engine speed, which will lead to larger available braking torque, while engine braking capability is rather low at low speed due to low engine speed. For the trucks that we tested,

since the service brake control activation deactivates the control of engine torque, engine braking torque and the service brake itself, we have deactivated the service brake control for most maneuvers except the coordinated braking control in emergency situation. Therefore, the deceleration needs to fully rely on the engine brake control since the truck does not have a transmission retarder. For those reasons, in the speed variation maneuver, the maximum deceleration is limited to 0.3 m/s^2 , and the maximum acceleration is below 0.1 m/s^2 . The following plots show the system's string stability related performance. The speed switching logic between the minimum 55 mph and maximum 65 mph in the test is as follows: once it reaches minimum or maximum speed, the CACC string will stay at that speed to cruise for one minute, and then it starts to switch to the other.

Since truck 1 is in CC mode and there is a virtual vehicle (defined as a vehicle running exactly with the reference trajectory) ahead of it, the reference trajectory planning is with respect to the virtual vehicle. Therefore, the control response is different from trucks 2 and 3, which are in CACC mode. i.e. the two following trucks use the information passed by the DSRC.

Table II.7.3 shows the maximum speed and distance tracking errors for 3-truck CACC speed variation maneuvers. It can be observed from the table that (a) the truck further behind has larger speed and distance tracking errors, reflecting the weak string stability characteristics; and (b) the maximum distance tracking error is nearly 2.5 m, which means that for highway maneuvers with the maximum acceleration and deceleration listed before, the following distance should not be closer than 10 m for safety. This is similar to the maximum distance tracking error for cut-in maneuvers observed before. However, the performance should be improved when the service brake automatic control deactivation problem can be resolved so that service brakes could be applied to provide a higher braking rate. Also, if the truck had a transmission retarder, the deceleration performance could be improved further.

Table II.7.3 Truck Speed Variation between 55 ~ 65 mph

Maneuver	D_Gap [m]	Vehicle Position	Speed Error [m/s]		Distance Error [m]	
			RMS	Max	RMS	Max
ACC Speed Variation	35	1	0.12	0.98	0.92	5.73
CACC Speed Variation	35	2	0.23	1.53	0.48	2.50
CACC Speed Variation	35	3	0.57	4.35	0.42	2.50

CACC Truck and Real-time Simulation In-the-Loop for Intersection Operation

We cannot make any conclusion for this part of work since it is ongoing due to delay of funding arrival. At this stage, we are still developing the system and the algorithm. However, the following summarize the progress of this part of work up to the end of December 2018:

- Renovated two of the three Freightliner trucks for automated control, which can be controlled from speed 0;
- Renovated one PC-104 control computer on one of the trucks;
- Renovated the interface with J-1939 Bus so that all the data reading and control command can be executed through J-1939;

Conclusions

Control Performance Analysis Based on Test Track Data

The data analysis has shown that there is still room for CACC performance improvements, which include but are not limited to: systematic fault detection and handling, reducing transient tracking errors for cut-in and cut-out maneuvers which involve sudden target distance changes, and for speed variations. These are unavoidable when the CACC string is operated in real-world traffic.

The results showed that the performance of the CACC system is reasonably robust and stable for constant speed following – the RMS speed tracking error was well within 0.1 m/s and the RMS distance tracking error was well within 0.3 m. It has been found out that some larger transient maximum distance tracking errors (about 2 m) were mainly caused by transitions between manual and automatic, which often happened at the very beginning or during the runs due to driver’s accidentally switching OFF and then ON the CACC mode.

Future work needed before full-scale public operation would include extensive testing of the CACC system with public traffic on a freeway corridor by commercial truck drivers while iteratively evaluating and improving the following aspects: (a) control performance and reliability in different traffic and road geometry, particularly, road grade; (b) quantitative fuel saving and emission reduction benefits in real-world traffic; and (c) driver acceptance and behaviors for using CACC trucks in public mixed-traffic operation.

CACC Truck and Real-time Simulation In-the-Loop for Intersection Operation

We cannot make any conclusion for this part of work since it is ongoing due to delay of funding arrival.

Key Publications

1. X. Y. Lu, S. Shladover, and S. Bergquist, Truck CACC implementation and test to verify control performance, accepted for TRB Annual Meeting, Jan. 2019, Washington, D. C.

Acknowledgements

The test data and part of the analysis were from the project funded jointly by DOE/VTO through EEMS Program and by Federal Highway Administration (FHWA) EAR Program with match funding from Caltrans. The CACC technical and system development was by FHWA EAR Program with match funding from Caltrans. Volvo USA provided truck and strong technical support to the CACC system development.

The work in Part (B) was sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The authors acknowledge Eric Rask of Argonne National Laboratory for leading the Connected and Automated Vehicles Pillar of the SMART Mobility Laboratory Consortium. The DOE Office of Energy Efficiency and Renewable Energy (EERE) managers played important roles in establishing the project concept, advancing implementation, and providing ongoing guidance.

II.8 CACC Development for Passenger Cars with Different Powertrains (LBNL) [Task 7A.3.1 Part II]

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Start Date: September 1, 2018	End Date: August 31, 2019	
Project Funding (FY18): \$300,000	DOE share: \$300,000	Non-DOE share: \$0

Project Introduction

Previous research and development on CACC (Cooperative Adaptive Cruise Control) at LBNL and PATH (also in the U.S. and internationally) were mainly focused on IC engine vehicles of the same type for transportation mobility purposes. CACC for vehicles of different types and different powertrains have not been developed and implemented, although the automatic control of vehicles with different power sources will be an important issue in energy savings for CACC. The work proposed here for DOE/VTO will develop the CACC string with at least three power types: IC engine (gasoline and/or diesel), hybrid electric, and fully electric, which offers many new possibilities. With this connected automated vehicle string platform, DOE/VTO can conduct extensive research and development and field test for data collection for energy saving and emission reduction studies in a long run. The collected data in real-world traffic can be used for calibration of microscopic simulation models for more accurate meso- and macroscopic level energy consumption and emission change evaluation.

This project is a joint effort of LBNL, ANL and INL. More specifically, for FY 2018:

The roles of the LBNL team will include:

- Develop PC-104 industrial computer and install Real-time operating system QNX
- Develop lower level software including interfaces with commercially available remote sensors (such as radar, lidar and video camera, or their combination), DSRC units and CAN Bus
- Preliminarily implement CACC algorithm on the 4 vehicles
- Conduct initial test with ANL and INL on a test track; candidate test tracks include: (a) GoMentum Station in California (<http://gomentumstation.net/>); and (b) Navy Air Station in Alameda, in California; both test sites are in the proximity of LBNL.

The roles the ANL team will include:

- Provide interface protocol with CAN Bus for real-time data reading and control of both driving torque and the brake
- Develop powertrain mapping for vehicles with different powertrain types
- Assist and coordinate with LBNL for CACC overall system development

Objectives

The objectives of this project for FY18 was to produce a preliminary design and develop CACC capability for a four-vehicle string. The CACC capability was required to employ at least three powertrain types. The target system was required to run on a test track at high speeds where the first vehicle operates using cruise control (CC). System test and demonstration was to be conducted on a closed track (if applicable).

Approach

The following approaches will be adopted to develop the system.

2. Develop Overall System Structure
3. Develop upper and lower control strategy and adopting previously developed suitable CACC algorithm for upper level control [\[1\]](#)
4. Develop remote sensor (radar and/or lidar) for target detection and tracking
5. Purchase and develop DSRC communication capability for V2V
6. Perform system integration
7. Perform initial system tuning and test at Richmond Field Station
8. Perform initial test and tuning for upper and lower level control for string stability of 4-car CACC on test track.

Results

Overall System Structure

The following Figure II.8.1 shows the overall system structure:

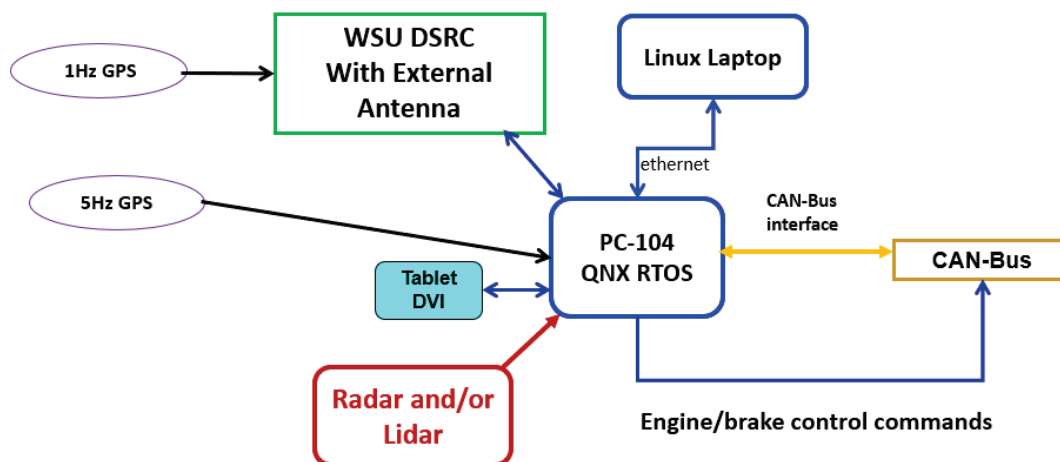


Figure II.8.1 Overall CACC system structure

The functionality is described as follows:

- PC-104: is an industrial control computer with real-time operating system (RTOS) QNX; it is most critical part of the overall system; it runs all the processes including the drivers for all the components and interfacing with CAN Bus
- Linux Laptop: this is for system development and tuning purposes since PC-104 does not have display by itself; the Linux laptop will act as the display and to run the highest-level script to execute the commands/processes on the PC-104 computer
- WSU DSRC (Wireless Unit for Dedicated Short Range Communication): is the hardware unit of 5.9 GHz wireless communication for V2V (vehicle-to-vehicle communication) capability, which needs a 1Hz GPS usually
- 5Hz GPS is to provide vehicle location with respect the ground (the earth)
- Radar/Lidar: is the remote sensor for front target detection and tracking and eventually to provide the target distance and relative speed which are to be used by the upper level control algorithm
- DVI (Driver Vehicle Interface): to be used for displaying any message/information to the driver and receiving any driver command such as driving mode (including: manual, ACC and CACC) and Time Gap selection etc.

Control System Structure

Figure II.8.2 depicts the CACC control software structure. The upper block includes the input data such as: remote sensor data for target detection/tracking and DSRC wireless communication data to determine the relative speed and distance. It also includes the driver command from DVI. The middle block is to use the output from the upper block to determine the desired acceleration/deceleration for vehicle following according to driver selected Time Gap and desired speed while maintaining string stability, which is the Upper Level Control. The lower block is the Lower Level Control which essentially convert the output of the Upper Level Control, i.e. the acceleration/deceleration, to engine torque control and brake control which are to be sent to CAN Bus for execution.

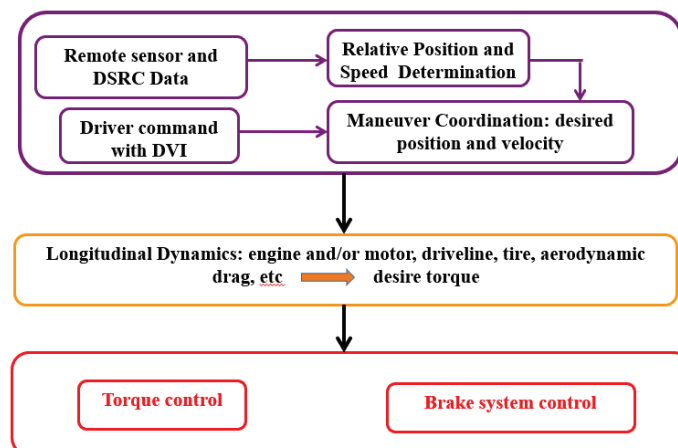


Figure II.8.2 Control System Structure

Vehicles to Be Used for CACC Development

The following Figure II.8.3 shows the types of vehicles to be used for the CACC development:

- Both the Honda Accord and Toyota Prius PHEV with ACC are Parallel Hybrid Powered vehicles with ACC (Adaptive Cruise Control) capability; the powertrain contains motors driving each wheel; the IC engine can also provide power to the front axle; the motor and engine can jointly provide power to the vehicle at the same time to generate large driving torque; the motors also act as generators in vehicle deceleration for energy economy
- The BMW i3 with ACC is Serial Hybrid in the sense that the vehicle is powered by motor only; the IC engine is only used to generate the electric to be used by the motor and stored in battery
- The Ford Taurus is a traditional IC engine powered vehicle.

Honda Accord PHEV with ACC



Prius Prime PHEV with ACC



BMW i3 with ACC and Traffic Assist



Ford Taurus 2.0L Ecoboost with ACC



Figure II.8.3 Vehicles to be used

Other progress of the project:

- LBNL team is currently working on the PC-104 computer, DSRC units, and remote sensors.
- ANL team has made one vehicle ready in the sense that the required CAN Bus data can be accessed and the vehicle torque can be controlled.
- It is expected that ANL will send two cars to LBNL in a few months for control system development.

Conclusions

The project began in September 2018 and has developed an overall system structure and an approach for the control structure.

References

1. Lu, X. Y. and S. E. Shladover, 2017, Integrated ACC and CACC Development for Heavy-Duty Truck Partial Automation, 2017 American Control Conference, May 24-26, Seattle, WA, USA

Acknowledgements

This project is sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The authors acknowledge Eric Rask of Argonne National Laboratory for leading the Connected and Automated Vehicles Pillar of the SMART Mobility Laboratory Consortium. The DOE Office of Energy Efficiency and Renewable Energy (EERE) managers played important roles in establishing the project concept, advancing implementation, and providing ongoing guidance.

II.9 Experimental Evaluation of Eco-Driving Strategies (LBNL) [Task 7A.3.2]

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Project Funding (FY18): \$100,000	DOE share: \$100,000	Non-DOE share: \$0

Project Introduction

Eco driving includes a broader set of strategies to reduce energy use in vehicles. Most of the studies to-date have been focused on individual scenarios and applications to reduce fuel consumption and exhaust emission. This project aims to identify through analysis of a broad set of Eco-driving scenarios to fully define the Eco driving strategies, and to prioritize those that could achieve higher energy efficiency and generate larger benefits. In the second year, the project will further evaluate eco-driving strategies through collection and analysis of the field data and experiments.

Objectives

To analytically and experimentally evaluate the energy saving benefits (to the subject vehicle and vehicles behind) and impacts (on efficiency and safety of surrounding traffic) by applying eco-driving strategies designed for human drivers and ACC-like driving.

Approach

The LBNL project team will conduct analyses to broadly assess Eco-driving strategies and applications in order to establish a foundational understanding of associated energy implications. The approaches for this task include:

- a) Evaluation of the potential opportunities for achieving Eco-Driving.
- b) We will assess the energy consumptions for light- and heavy-duty vehicles for various operation scenarios from the perspectives of driving cycle to identify the potential opportunities for energy savings and their priorities.
- c) Study of Eco-Driving strategies and applications.
- d) Various Eco-driving strategies will be analyzed against the energy saving opportunities identified under sub-task (a). A broader set of strategies for full range of Eco-driving application scenarios will be studied. Examples of these strategies may include vehicle feedback devices (smart gauge, eco assist displays, and phone apps), Eco approach and departure at intersections, curve speed warning, real-time traffic alert, Eco route guidance, platooning (reduction of aerodynamic drag), etc. This analysis will be built upon the study under RQ1.1 (Define CAV concepts and time frames for adoption), which provides two examples of Eco-driving application scenario, including infrastructure-to-vehicle (I2V) cooperative eco-driving support for Level 0 manually driven vehicles and urban eco-signal control with I2V

communication to vehicles. The systematic evaluation of Eco-driving strategies will enable us to fully define the Eco-driving strategies and their applications. This study will build the foundation for the follow-on research and experimental studies under this task.

- e) Assessment of current development of the Eco-driving applications.
- f) Conduct a thorough literature review to assess the state-of-the-art studies and developments for eco-driving applications. A significant portion of the existing studies have been concentrating on a limited number of Eco-driving strategies, including Eco approach and departure and platooning. We will review these plus others to include the full breath of eco-driving approaches, and assess the results (the benefits and impacts) obtained from these studies to determine the areas where sufficient knowledge exists and the gaps in each application area. Analysis will be conducted to evaluate how to address these gaps.

Results

Under task (a) the assessment will be conducted from two perspectives:

1) Assessment of Energy Dissipation for City and Highway Driving

The energy dissipation for vehicles need is studied first in order to identify the potential opportunities for energy savings and their priorities. Assessment is conducted quantitatively on energy dissipation for entire driving duty cycles that include both urban and highway driving.

While the energy losses for cars and heavy vehicles may occur in the forms of engine losses, drive train losses, parasitic losses, auxiliary electrical losses, and power to wheels losses [1], [2], [4], Eco-Driving using ITS related technologies can potentially address improvements of power to wheels efficiency, i.e., to reduce unnecessary acceleration and braking, as well as wind resistance by application of controls or influencing driver's behaviors. The assessment conducted under this task defines the areas where Eco-Driving strategies may contribute to fuel savings (i.e., to minimize possibly engine losses during extended driving time including idling for combustion engine vehicles and lower speed operation), as well as a boundary fuel savings enabled by Eco-Driving.

2) Trip Decomposition and Fuel Consumption Estimation

We further conducted analysis of trips in order to understand the scenarios and the unnecessary of wasteful fuel consumptions and to identify energy saving opportunities. For this purpose, we start with decomposing the trips and analyzing the energy consumption distributions. We categorize fuel consumption into two types, i.e., the baseline fuel consumption and unproductive fuel consumption.

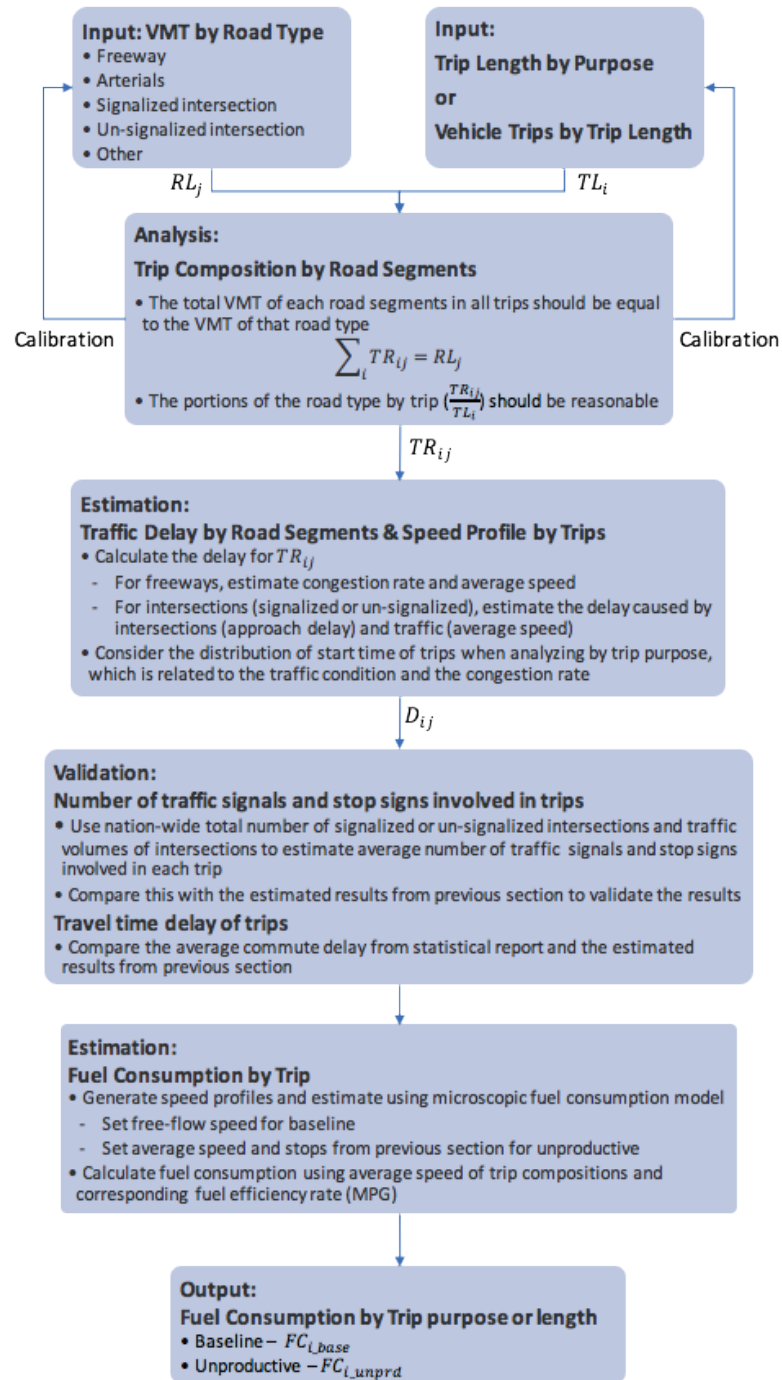
The baseline (productive) energy consumption is defined as the energy necessary to operate a vehicle following the maximum speed limits (at which a vehicle may legally travel on a particular stretch of road) to accomplish a prescribed trip mission. Whereas unproductive energy consumption is the energy consumed in addition to the baseline energy consumption due to unnecessary decelerations, accelerations, speeds lower than prescribed speed limit and stops.

The variation in vehicle characteristics may result in differences of the fuel consumption but it only contributes to the vehicle-based baseline fuel consumption, On the other hand, unproductive fuel consumption occurred due to vehicle deceleration and acceleration and unnecessary stops where stops are not always warranted (e.g., stop at red), and change of the speed (i.e., unnecessary braking and fast accelerations) where constant speed is designed. The scenarios that involve unproductive fuel consumptions may include:

- On freeway – traffic congestion and incident caused shockwave or fluctuations of speed
- On arterial highways, traffic congestion,

- At signalized intersection – traffic or queue, signal control, speed
- At un-signalized intersection –stop signs, traffic queue, pedestrians
- Others – speed limit, pedestrian crossing, grade

We have developed an approach for the analyses as shown in Figure II.9.1 Four main steps needed to assess the energy consumptions for various operation scenarios from the perspectives of trips. The first step is to analyze the trip composition by road segments using statistics, including the Vehicle Miles Traveled (VMT) by road type and the trip length by trip purpose or the trip length distribution [4]. Then traffic delays by trips are estimated in the next step [5], [6]. In the third step, the fuel consumptions by trips are estimated based on the results from the previous part. As the final step, the fuel consumptions of different trip purposes or different trip lengths, including baseline and unproductive consumptions, are put together to identify the potential opportunities for energy savings and their priorities. The team has begun the analyses following the approach defined in Figure II.9.1 and plan to have this work done by March 2019.



Notations:
i indicates the trip purpose or length bin, $i \in \{To/from\ work, Work - related\ business, Shopping, Other\ family/ personal\ errands, School/church, Social/recreation, Other\}$ when analyzing by trip purpose, $i \in \{< 5mi, 5 - 10mi, 10 - 15mi, 15 - 20mi, 20 - 30mi, > 30mi\}$ when analyzing by trip length
j indicates the road type, $j \in \{Freeway, Arterials, Signalized\ intersection, Un - signalized\ intersection, Other\}$
 TL_i is the average trip length of the trip purpose or length *i*, unit: mi
 RL_j is the vehicle miles traveled (VMT) on the road type *j*, unit: mi
 TR_{ij} is the average length of the trip purpose or length *i* traveled on the road type *j*, unit: mi
 D_{ij} is the average delay of the trip purpose or length *i* traveled on the road type *j*, unit: s
 FC_{i_base} is the baseline fuel consumption of the trip purpose or length *i* traveled, unit: ml
 FC_{i_unprd} is the unproductive fuel consumption of the trip purpose or length *i* traveled, unit: ml

Figure II.9.1 Flowchart for Estimating Fuel Consumptions of Trips

Conclusions

This project started in June 2018 and no conclusions have been reached by September 2018.

References

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II.10 Understanding CAVs in Automated Mobility Districts (INL, NREL) [Task 3.3.2]

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Start Date: October 1, 2017	End Date: September 30, 2018	
Project Funding (FY18): \$150,000	DOE share: \$150,000	Non-DOE share: \$0

Project Introduction

Automated electric shuttles and other automated or autonomous vehicles show promise to reduce fuel consumption by reducing personally owned vehicle operation and substitution of electricity for petroleum fuel while increasing mobility in several conceptual implementations. Fully autonomous vehicle systems have many challenges to overcome before they can operate, at scale, at level 4 or level 5 automation on public streets and highways. In the near term, the concept of automated mobility districts, campus-sized areas designed with special considerations for vehicles using CAV technologies, may provide opportunities for automated electric vehicle transportation.

Objectives

The nature of such automated mobility districts makes them well suited as early test beds from which data can be gathered to better understand the implications of CAVs technologies on energy consumption and mobility. The information produced will be provided to SMART mobility modeling efforts to better predict mobility energy productivity in future scenarios.

Approach

This task has sought to partner with early testing/implementation of automated electric shuttles that are being contemplated or pursued in various neighborhood, military base and campus settings around the country. One early implementation of automated electric shuttles operating in a campus setting was identified at University of Michigan as part of their Mcity Driverless Shuttle pilot, detailed in a case study report [\[1\]](#). Mcity researchers agreed to work with INL researchers to collect charging energy data to complement their behavior-based study of human interactions with the automated shuttles. Precision energy metering hardware was installed in each of the branch circuits used exclusively to charge the shuttles, and the devices were networked to allow for remote access to the data. Mcity researchers, as part of their study, collected travel path data on each of the shuttles. These data streams are shared, and the reduced data is joined to provide a daily snapshot of energy consumption and the routes travelled. Because the automated shuttles are on a fixed route, sensitivities affecting energy consumption of vehicles, such as weather or speed profile, can be explored.

Results

The Mcity automated electric shuttles were launched in June, 2018. While data were collected continuously since the launch, only a sample of travel data was available for analysis in advance of completion of Mcity’s researcher data portal, which will allow full access to the data at the end of FY-18. Complete analysis of the data will follow, and the preliminary analysis based on the one-week sample of travel data provided in the meantime is summarized here.

The shuttles’ top speed was observed to be around 10 MPH on the two-stop route with a round trip distance of 1.2 miles. The vehicles have seats for 10 passengers plus one conductor. The route was electronically mapped, and the vehicles are limited to self-driving operation on the assigned route. Summary data from a summer day of operation in July is detailed in the table below.

Table II.10.1 Operational Data Details – July 17, 2018

Shuttle ID	Distance Travelled (Mi)	Recharge Energy (kWh)	Operating Time (hr)	AC Recharge Energy (Wh/Mi)
Shuttle 54	16.5	31.1	4.3	1883
Shuttle 56	19.5	32.5	5.5	1668

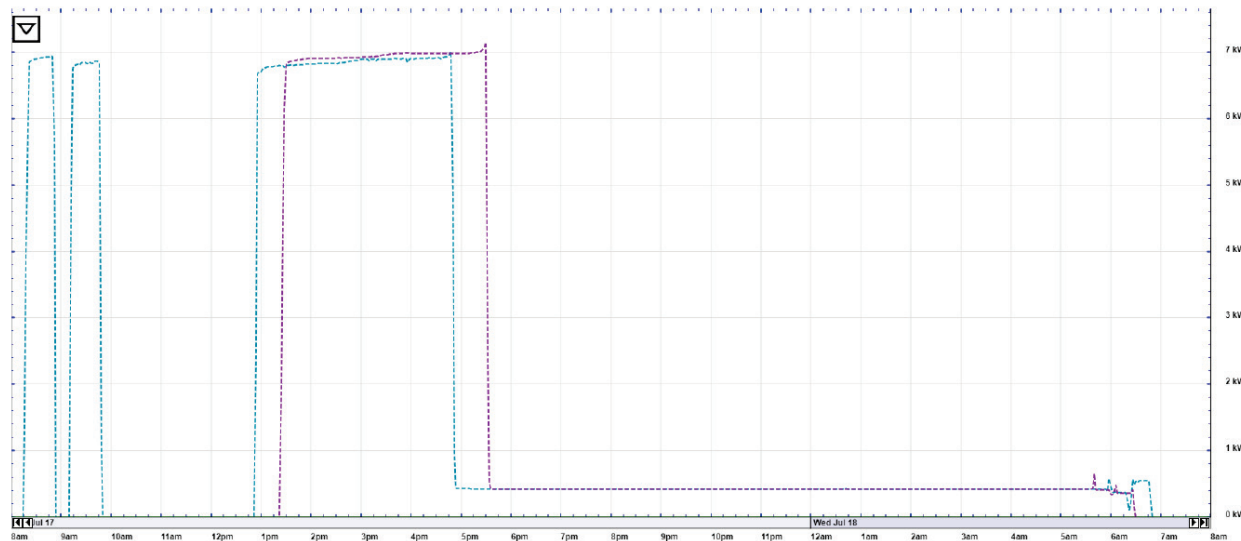


Figure II.10.1 Power data from the two shuttle charging circuits over a 24-hr period is shown

Future analysis will provide a distribution of energy usage over a range of daily weather conditions and varying speed traces due to interaction with traffic on the route. This analysis will explore the changes in energy usage and investigate sensitivities that affect the vehicles’ efficiency.

Conclusions

The test data analyzed to date represents an early automated shuttle deployment, and the magnitude of the vehicles’ energy use likely reflects technology that is not fully matured. The early analysis shows that these 10-seat vehicles have high energy usage, consuming about 80% of the electrical energy of a 35-seat electric transit bus [2]. Large ancillary loads coupled with slow average speed is likely a contributing factor. Both the climate control system and self-driving functionality are expected to be large ancillary loads, though only the self-driving hardware is unique, compared to transit and personal electric vehicles. Future work could further

determine the share of energy consumed by each sub-system, and investigation of other vehicle types under varying routes will also improve understanding of automated vehicles' energy impacts. The project team additionally made connections with other sites that are starting or will soon start deploying automated shuttles, which may additionally enable future comparison of energy consumption data between different vehicle types and locations. Test data from this task (including energy consumption, along with driving behavior) are useful to other efforts contemplating district- or campus-based automated shuttle operation, and particularly will be shared with the SMART Mobility Urban Science task (US 2.4.1) developing the Automated Mobility District modeling and simulation toolkit.

References

1. "Mcity Driverless Shuttle, A Case Study," University of Michigan, accessed September 24, 2018, <https://mcity.umich.edu/wp-content/uploads/2018/09/mcity-driverless-shuttle-case-study.pdf>.
2. "Foothill Transit Battery Electric Bus Demonstration Results", National Renewable Energy Laboratory, accessed September 3, 2018, <https://www.nrel.gov/docs/fy16osti/65274.pdf>.

Acknowledgements

This evaluation would not have been possible without the cooperation and data sharing of researchers at University of Michigan's Mcity.

II.11 Focused Validation of Select SMART Simulation Activities (ANL) [Task 7A.3.4]

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Start Date: September 29, 2017	End Date: September 28, 2018	
Project Funding (FY18): \$200,000	DOE share: \$200,000	Non-DOE share: \$0

Project Introduction

While originally intended to provide validation for specific SMART related project, this work has been re-scoped somewhat in the current Fiscal Year due to delays in coordinating, obtaining data, and finalizing experiment plans across the various SMART projects. While additional efforts will be spent towards specific validation in future years, this year's focus was on 1) validating and investigating several highlighted CAV impact studies used in previous DOE bounding analysis and 2) investigating additional items related to field-collected data in terms of desired collection rate and related parameters.

Objectives

- Validate previous CAV impacts drawn from earlier literature and bounding reports
- Aid in validation of specific SMART research projects (in collaboration with PIs)
- Utilize Argonne's research fleet of instrumented CONV., HEV, PHEV & BEVs and historical data repository for evaluation of data quality/sampling sensitivities and possibilities for expanded data collection



Approach

Dynamometer based testing of A-to-B drive-cycles (CAV to non-CAV behaviors) with sufficient repeats to draw meaningful conclusions across multiple powertrain types combined with historical analysis of Argonne's data repository spanning multiple vehicle and powertrain types across regulatory and real-world driving conditions.

The test vehicles used for the reference validation study were a 2017 Ford F150 with a 3.5L V6 and 10-speed automatic transmission and 2017 Toyota Prius Prime HEV with a 1.8L I4 and a power-split transmission coupled to the engine with a one-way clutch. For the purposes of this study, the Toyota Prius Prime was considered a HEV when in charge sustaining mode and a BEV when in charge depleting mode (due to its full

EV operating capability). The Ford F150 was considered an advanced conventional vehicle and a conventional vehicle with idle stop-start capability, depending on whether the idle stop-start function was enabled or not. More detailed specifications for each vehicle are presented in the table below.

TABLE II.11.1 Test Vehicle Specifications

		
Test Vehicle	2017 Ford F150	2017 Toyota Prius Prime
Architecture	Conventional ICE Vehicle	Plug in Hybrid Vehicle
Engine	3.5 liter Turbo, V6, DOHC 24V, 280 kW (375 hp) @ 5,000 rpm 637 Nm (470 lb-ft) @ 3,500 rpm	1.8L, Inline 4-cylinder, 72kW (96hp)@5200rpm, 142Nm (105 lb-ft) @ 3600rpmL
Transmission	Four wheel drive 10-speed automatic transmission Final Drive 3.21	Front Wheel Drive Power split w/ one-way engine clutch
Motor	N/A	MG1: 23kw (31hp), 40Nm (30 lb-ft) MG2: 53kw (71hp), 163Nm (120 lb-ft)
Battery	N/A	Li-ion, 350 V, 25 Ah 8.8 kWh net capacity
EPA Label Fuel Economy (mpg)	17 City / 23 Hwy / 20 Combined (4WD option)	55 City / 53 Hwy / 54 Combined

Results

Validation of Highlighted CAV References

Test cycles completed on the dynamometer included a series of intersection approach and launch speed traces based on the simulation studies by Barth et al. and Li et al. The first drive cycle was based on the study by Barth et al. and included four different intersection approach and launch speed profiles. Each of the four vehicle speed profiles corresponds to a different intersection approach and launch strategy. A diagram of the intersection approach scenario for this situation is shown in the figure below.

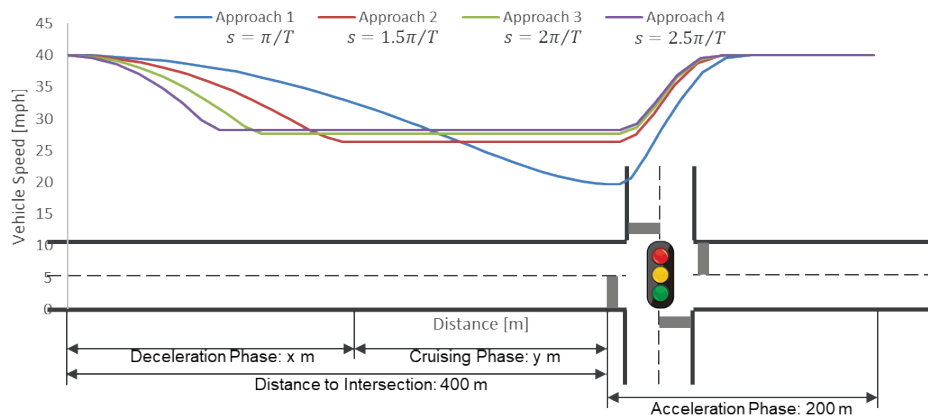


Figure II.11.1 Intersection eco-approach and launch with no stop required (Situation 1)

In order to effectively measure the fuel and energy consumption for each of the four different speed profiles, a custom drive cycle was created with 30 consecutive repeats of each one. The average of the 30 repeats was then used for comparison of the different approach and launch strategies.

The fuel and energy consumption for four different eco-driving strategies in an intersection scenario described by Situation 1 are presented below. The experimental results include fuel and energy consumption for the four approach and launch strategies shown above, across three different powertrain types. The figure below summarizes the relative fuel and energy consumption for approach strategies 2 through 4, compared to approach 1.

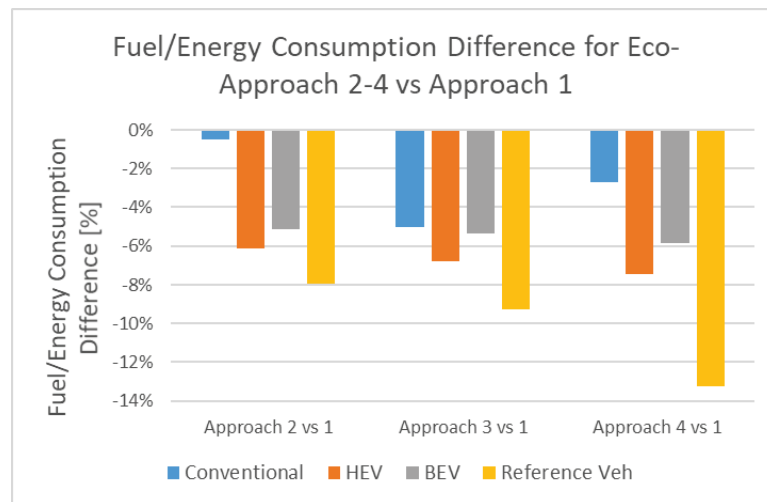


Figure II.11.2 Summary of the relative fuel and energy consumption for approach strategies 2 through 4 for Situation 1

The second drive cycle used for this study was based on the paper by Li et al. and consists of three different speed profiles for approaching an intersection where a complete stop is required and approach distance is long enough to coast to a stop. The intersection scenario and the three different speed profiles used for this study are shown below.

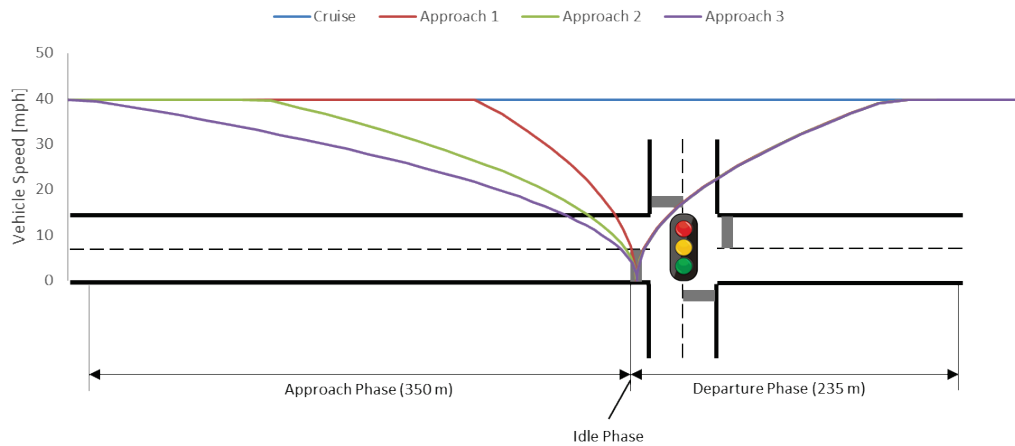


Figure II.11.3 Intersection eco-approach with stop and idle required (Situation 2)

In addition to the three approach and launch speed profiles, a constant speed cruise was also added to the beginning of the drive cycle in order to obtain a measure of the best possible fuel consumption by cruising through the intersection without stopping. The constant speed cruise was set to 17.8 m/s (40 mph) and ran for total of 5.85 km (3.64 mi), equivalent to 10 times the distance of a single intersection approach and launch speed profile. Following the constant speed cruise, the rest of the drive cycle was made up of 10 consecutive repeats of each of the three different approach and launch speed profiles, representing different approach strategies for situation 2 from the Discussion of Eco-Driving Strategies section. The fuel and energy consumption for the constant speed cruise and each of the three different approach and launch strategies was then determined from the average value of the 10 repeats.

The fuel and energy consumption for the three different approach strategies shown are shown below for Situation 2. The first figure shows a summary of the relative fuel and energy consumption of all four powertrain types for approach strategies 1 through 3 compared to cruising through the intersection on a green light without stopping. The second figure is a summary of the relative fuel and energy consumption of approach strategies 2 and 3 compared to approach 1, representing the potential benefits of eco-driving from connected and automated vehicles compared to identical, human driven vehicles.

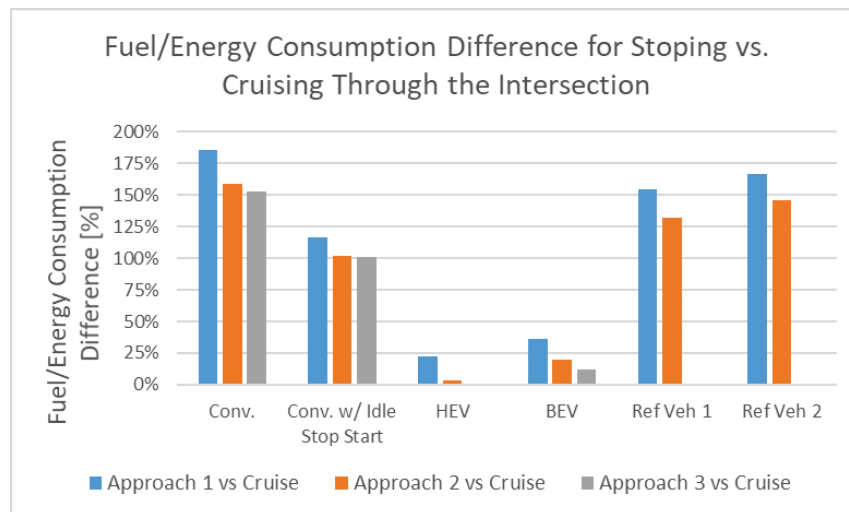


Figure II.11.4 Summary of the relative fuel and energy consumption of approach strategies 1 through 3 compared to cruising through the intersection without stopping for Situation 2

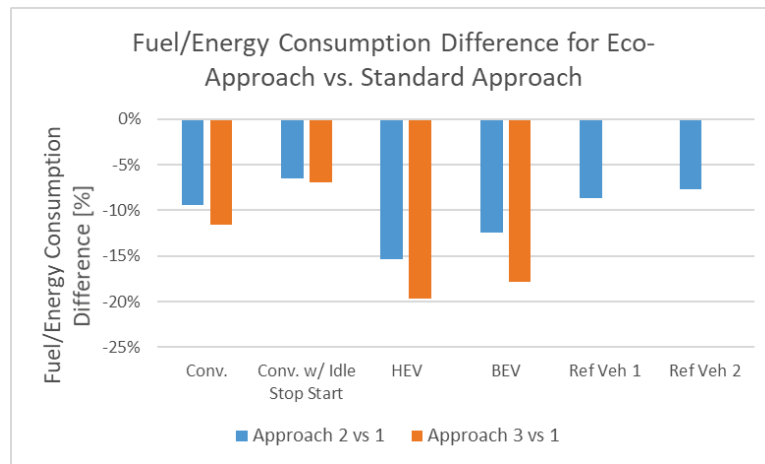


Figure II.11.5 Summary of the relative fuel and energy consumption of approach strategies 2 and 3 compared to approach 1 for Situation 2

Sampling Rate Investigation

The figure below highlights the main issue observed related to sampling rate observed across several vehicles and drive-cycles done in the laboratory at Argonne. Specifically, the figure below highlights the loss of information as acquisition rate decreases. While the loss of resolution and thus miscalculation of energy varies from cycle-to-cycle, this observation was similar across a range of relevant drive cycles. In the plot below, 1Hz is shown in black (the line showing underrepresented peaks), despite 1 Hz often being used as a default acquisition rate in many in-field data collection projects. Summary recommendations regarding collection rate are shown in the conclusions below.

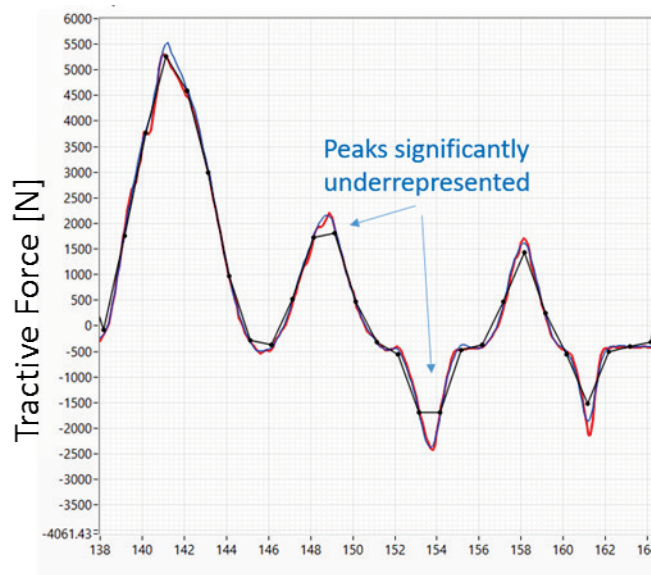


Figure II.11.6 Loss of information due to decreased sampling rate

Conclusions

- Eco-Situation 1 - For the advanced conventional vehicle, approach strategy 2 had very little fuel consumption benefit when compared to approach 1, while approach strategies 3 and 4 showed more significant benefits of 5% and 3%, respectively. The HEV and BEV powertrain types showed significant benefits for fuel and energy consumption and increased slightly between approach 2 and 4. Similarly, the

reference results also show an increasing benefit between approach 2 and 4 when compared to approach 1. It should be noted that the absolute value of the reference benefits is significantly higher than the experimental test results for all of the powertrain types tested, suggesting more recent vehicle developments may have altered the expected benefits from certain CAV strategies.

- Eco-Situation 2 - Comparing eco-approach strategies to standard intersection approach by human drivers, electrified vehicles again have higher relative fuel/energy consumption benefits than conventional vehicles. The HEV and BEV enjoy fuel and energy consumption benefits of 12-20% thanks to eco-approach, with the higher benefits realized by the HEV. The conventional vehicles, on the other hand, see fuel consumption benefits of 7-12%, with the higher benefits attained by the vehicle without idle stop-start technology.
- 1 Hz data appears insufficient for many “energy” based calculations and assessments from on-road data due to omissions of significant peaks and valleys related to the sampling rate. It appears that 2-2.5 Hz may provide acceptable results for signals that are relatively clean (i.e. direct torque/power measurement), but collection rates closer to 4 Hz may be needed to translate noise data such as GPS information into energy-relevant numbers (i.e. force and tractive power)

Key Publications

1. “QUALITATIVE ANALYSIS AND EXPERIMENTAL RESULTS OF ECO-DRIVING STRATEGIES FOR DIFFERENT POWERTRAIN TYPES AND SCENARIOS”, 2019 TRB Presentation.

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1. Barth, Matthew, et al. "Dynamic ECO-driving for arterial corridors." *Integrated and Sustainable Transportation System (FISTS), 2011 IEEE Forum on*. IEEE, 2011.
2. Li, Meng, et al. "Traffic energy and emission reductions at signalized intersections: a study of the benefits of advanced driver information." *International Journal of Intelligent Transportation Systems Research* 7.1 (2009): 49-58.

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III SMART Mobility - Mobility Decision Science (MDS)

III.1 WholeTraveler Study (LBNL, NREL, INL) [Task 1.0]

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Start Date: October 1, 2016	End Date: September 30, 2019
Project Funding (FY18): \$3,300,000	DOE share: \$3,300,000 Non-DOE share: \$0

Project Introduction

The WholeTraveler Transportation Behavior 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 survey was 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 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.

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.
2. What are the energy implications in the transportation system of these demand curves (barriers and drivers)?
 - 2.1. 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?
- 2.2. 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?
 3. 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?
 - 3.1. 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)
 4. What are the dynamic lifecycle drivers and barriers to transportation decisions and their long-term energy implications?
 - 4.1. 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?
 - 4.2. How do change points in lifecycle phases drive changes in transportation choices (vehicle ownership and mode use)?
 - 4.3. 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?
 5. 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?
 6. 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?
 7. 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?
 8. 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 varies 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) are 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

Data collection is complete and we exceeded our targets of 900 Phase 1 responses and 200 Phase 2 responses. Specifically, invitation letters were sent to 60,000 active residential mailing addresses in this study area, encouraging potential participants to go to a designated website to fill in the Phase 1 survey. A single reminder postcard followed up this initial letter. The Phase 1 survey was administered online only, and took a median of 27 minutes to complete. Upon completion of the Phase 1 survey, respondents were invited to participate in Phase 2. Those that opted in to Phase 2 were 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 were provided for the respondents to download an archive of their Google Location History, and upload it to a web tool that enabled them to select the date range of the data they agreed to submit, respond to a short series of questions, and transfer the data to a Lawrence Berkeley National Laboratory secure server. Respondents that completed Phase 1 were provided with a \$10 Amazon gift card, and those that complete Phase 2 were provided with an additional \$20 Amazon gift card. The response rate was 1.7% for the Phase 1 survey, resulting in about 997 complete responses and an additional 48 responses that completed the entire survey other than the life history calendar. The final number of these respondents that subsequently followed through and completed Phase 2 as well was 301.

We have started conducting analyses of these data to tackle the first round of pressing questions. The two sets of results generated with the data thus far are summarized below. These results were generated using the Phase 1 data only, and in particular only the first 915 complete survey responses from Phase 1. These will be updated with the final set of responses included.

Conclusions

Following a process of comprehensive background research informing the development of a methodologically rigorous two-phase survey strategy during the first year of the project, the WholeTraveler team completed data collection in July 2018. Throughout the process, the research team has been focused on identifying opportunities to produce and distribute high-impact findings of this project, and to support related projects within the SMART Mobility portfolio. In contribution toward these objectives, the WholeTraveler team produced two invited papers that were submitted to the journal *Transportation Research Part D: Transport and Environment*. Key findings are presented in the following.

The first paper is entitled, “How to reach the users: Evaluating what characteristics indicate adoption of energy efficient transportation solutions in the face of rapid transformation”. This paper explores several characteristics of WholeTraveler respondents, and identifies two primary groups of adopters of emerging transportation technology. Based on classic diffusion adoption theory, the team differentiated respondents into categories of initial adopters and potential adopters. Findings identified age, income, education, presence of children in the household, mode characteristic preferences, personality characteristics, and location qualities as predictors of adoption of emerging transportation technologies. Evaluation included a focus on three emerging transportation technologies and services: ride-hailing (either shared/ carpool or individual passenger), alternative

fuel vehicles (hybrids and plug-in electric vehicles (PEVs)), and three different levels of automated vehicle (AV) technologies.

Some key insights gained from this analysis:

- The carpool option of ride-hail services provides valuable accessibility to emerging transportation options for those that can't take advantage of many of the other technological innovations
- Having a young child of an age requiring a car seat or other specialized restraint, as well as being an introvert, both present barriers to diffusion potential of ride-hailing services
- Those with disabilities or illnesses preventing them from driving do not currently view fully automated vehicles as a solution to mobility constraints
- Those with relatively long commutes (up to 50 miles) are disproportionately more likely to adopt PEVs, suggesting that range anxiety does not appear to be binding for these commute distances
- The populations that make up initial adopters (innovators and early adopters) look very different in many instances than the population of potential adopters (when early majority are also included). In particular, age ranges of current adopters differ significantly from those with a high diffusion potential of innovated vehicle technologies (PEV and AVs), with younger cohorts not yet able to adopt these technologies, but highly interested in doing so in the future.

The data revealed that potential adopters possess different qualities and characteristics from initial adopters, suggesting that in order for adoption to advance beyond the smaller group of initial adopters to a larger population of potential adopters, more information, intervention strategies, and other behavioral levers must be identified and adjusted to encourage participation within the potential adopters group. However, Figure III.1.1 illustrates that the portion of respondents interested in adoption of several emerging technologies is substantial, with potential to shift toward adoption if adequately supported.

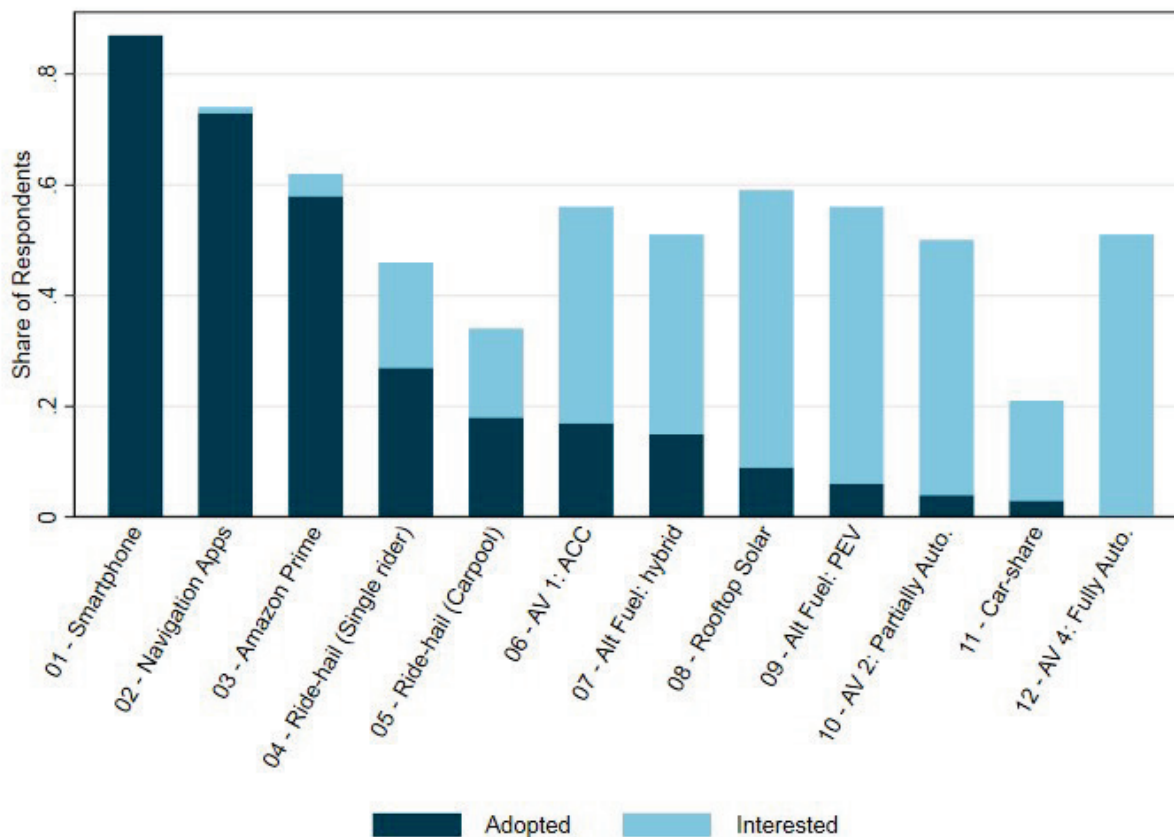


Figure III.1.1 Phase of diffusion and diffusion potential in the population by technology/service. Source: LBNL, NREL, and INL Joint Study)

The second paper focuses more closely on a specific demographic characteristic identified as a substantial limiter to adoption of emerging transportation technologies in the preceding paper, and is entitled, “Children at home: a barrier and driver of sustainable mobility patterns in the San Francisco Bay Area”. This inquiry used the novel life history approach to examining transportation choice over the course of life events, embodied in the WholeTraveler data collection effort. This analysis revealed that day-to-day mode choices are triggered by different family life stages defined by stages of development of the household’s children. It also showed that having children has a significantly different impact on transportation choices depending on the age at which the parent has their first child. With regard to transportation behavior, having children is associated with relatively more energy intensive transportation choices, generally increasing reliance on motorized modes, while reducing the extent to which parents use public transit and walking or biking. Additionally, children represent a barrier to being able to take advantage of ride-hailing. Although the timing of this doesn’t necessarily correspond to car seat requirements, but rather appears to correspond more to when children are over eight years of age.

However, the act of having children by itself is associated with other factors that affect transportation behavior, with shifts toward more car driving. Processes in preparing to have children, referred to as nesting, as well as the association with aging – getting older is a part of being a parent – and having children also contribute to barriers in adopting emerging transportation technologies. These effects differ with the age of parents at the birth of a first child, with younger parents driving less and using ride-hailing more as compared to older parents. Older parents apparently change their behavior less than younger parents, possibly related to aforementioned age effects that coincide with higher dependence on driving. A simplified table of the effects

of transitions between family stages and mode use behavior is shown in Table III.1.1. See paper for more details.

Table III.1.1 The Effect of Transitions between Family Stages on Mode Use Behavior

Family Stage \ Mode Use	(1) drove	(2) public	Text(3) ride-hailing	(4) walk or bike	Number of modes used
nesting	0.0404* (0.0227)	-0.0122 (0.0335)	-0.00703 (0.0663)	-0.0187 (0.0303)	0.0108 (0.0292)
children	-0.00587 (0.0202)	-0.106** (0.0330)	-0.0437 (0.0682)	-0.0672* (0.0295)	-0.102** (0.0296)
children (>8yr)	-0.00587 (0.0202)	-0.106** (0.0330)	-0.0437 (0.0682)	-0.0672* (0.0295)	-0.102** (0.0296)
children (>18yr)	0.0296 (0.0501)	-0.103 (0.0857)	-0.0979 (0.135)	-0.0238 (0.0830)	-0.0464 (0.0508)
Adj. R-sq	0.472	0.398	0.437	0.432	0.585
#people	731	592	198	567	878

Standard errors clustered at the person level in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

In addition to the preceding papers, the WholeTraveler team is working to provide data outputs and a de-identified version of the dataset to other SMART Mobility researchers to inform related and ongoing projects. Coordination with researchers within each of the other pillars and among several national labs is ongoing.

Key Publications

1. Spurlock, C. Anna, Victor Walker, James Sears, Gabrielle Wong-Parodi, Ling Jin, Margaret Taylor, Annika Todd, Andrew Duvall, Anand Gopal. *How to reach the users: Evaluating what characteristics indicate adoption of energy efficient transportation solutions in the face of rapid transformation.* Transportation Research Part D: Transport and Environment. In review.
2. Todd, Annika, Margaret Taylor, Ling Jin, Gabrielle Wong-Parodi, Victor Walker, James Sears, Anand Gopal, and C. Anna Spurlock. *Children at home: a barrier and driver of sustainable mobility patterns in the San Francisco Bay Area.* Transportation Research Part D: Transport and Environment. In review.

III.2 MA3T-MC on Market Dynamics Analysis

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Start Date: October 01, 2017 End Date: September 30, 2019
Project Funding (FY18): \$200,000 DOE share: \$200,000 Non-DOE share: \$0

Project Introduction

New smart mobility solutions are emerging in the transportation sector, including electrification, automation, and sharing. These solutions provide opportunities to improve energy productivity and security. For example, the electrification could displace conventional fuel usage, the automation could significantly improve vehicle operational efficiency, and the sharing could potentially increase vehicle occupancy. To understand their energy impact, it is important to evaluate their technology acceptance that could be affected by technological and behavior factors. Therefore, this project aims to use a vehicle and mobility choice modeling approach to explore consumers' behavioral factors and technological opportunities to facilitate the transition to transportation electrification, sharing and automation. In particular, this project will improve the inputs, assumptions, and choice structures of the Market Acceptance of Advanced Automotive Technologies-Mobility Choice (MA3T-MC) model. The core of the model is a multinomial nested logit model that simulates consumers' vehicle choices (buy new vehicles or not, and buy human-driven vehicles (HV) or fully-automated vehicles (AV)) and mobility choices (primarily using personal vehicles, TNC with HVs, TNC with AVs, or public transit). Scenario results of technology acceptance of different vehicle and mobility choices from this study could facilitate other SMART research.

Objectives

The objectives of this project are to 1) understand behavioral factors and technological opportunities to accelerate transition to transportation electrification, automation, and sharing, and 2) model consumer mid-term and long-term consumer choices of vehicle and mobility technologies with a focus on energy implications.

Approach

In this project, we will firstly finalize the MA3T-MC model with completed modeling structure and preliminary inputs and assumptions to be able to simulate long-term vehicle choices and mid-term mobility choices. Then, the behavioral parameters of the MA3T-MC model will be calibrated to SMART studies, historical and stated-preference data, including sales, TNC/mode choice demand, WholeTraveler observation and/or other surveys. Finally, we will use the MA3T-MC model to generate scenario results to facilitate SMART research.

Results

In FY18, to model heterogeneous travel behaviors, we focused on the segmentation of travelers. The 2017 National Household Travel Survey (NHTS) data are used for the clustering. Among multiple attribute categories available in the NHTS data, we select 10 attribute categories that potentially better affect consumers' acceptance of different mobility choices. Figure III.2.1 shows the structure tree with 10 levels of attribute categories. These attribute categories could potentially capture the differences in consumers' acceptance of different vehicle and mobility choices. For example, the vehicle ownership attribute is a key factor in consumers' purchase decisions of EVs. The medical condition affects purchase decisions of CAVs. Finally, the combination of both driving intensity and commute distance provides additional information on daily driving behaviors of travelers.

The full segmentation structure tree in Figure III.2.1 could potentially grow to an extremely large size when a high dimension of attribute categories is considered. Therefore, in FY18, we developed an object-weighted K-Mode clustering algorithm for reducing the segmentation size. The clustering algorithm is based on the classical frequency-based K-Mode clustering algorithm that minimizes the total dissimilarity cost of all households relative to their assigned segments. To better reflect difference in household weights in the NHTS dataset, we also introduce a weighting factor for each household in the clustering algorithm. We implemented the algorithm in Java. By considering different segment sizes, we finally clustered the entire NHTS household dataset into 7,238 segments. These segments are used in MA3T-MC model for simulating technology acceptance of different vehicle and mobility choices.

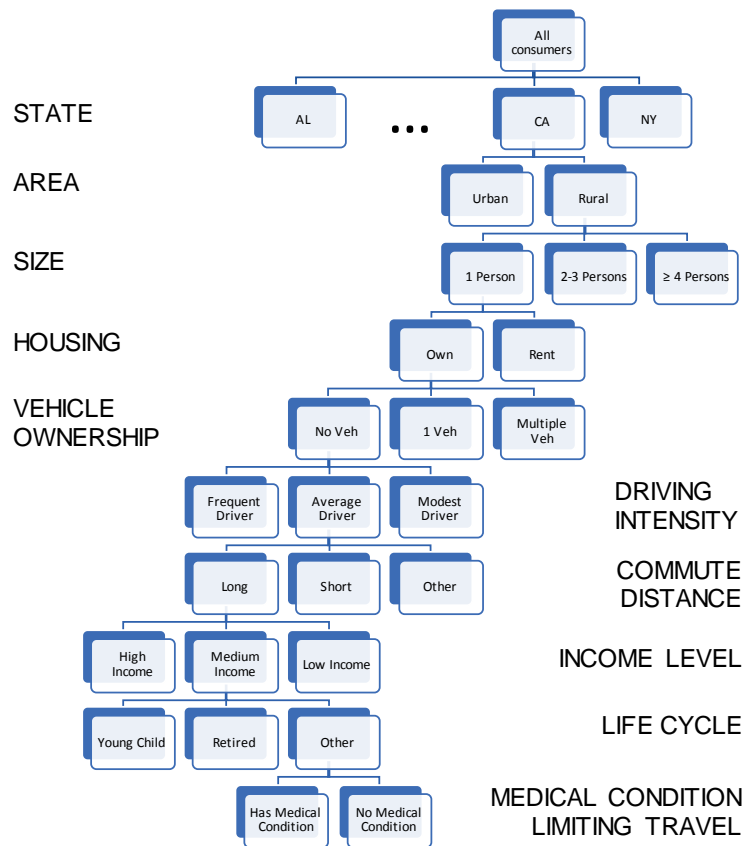
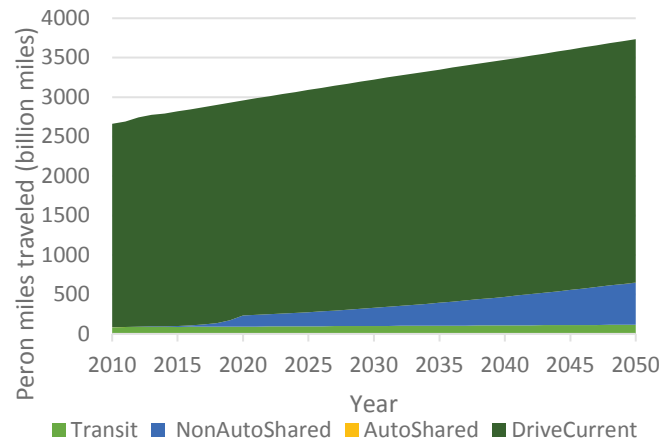
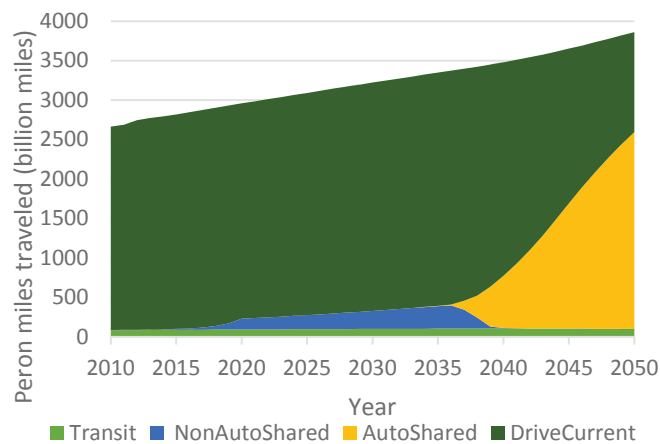


Figure III.2.1 Segmentation structure tree for modeling traveler heterogeneity

We also calibrated the MA3T-MC model using the NHTS data on mode choice. In particular, the shares of person miles traveled (PMTs) by transportation modes (i.e., transit, personal vehicle, and ride-hailing) are used for the calibration. With preliminary assumptions and inputs on technology (e.g., cost and fuel economy), infrastructure (e.g., fuel cost), and mobility characteristics (e.g., waiting and access time for different mobility choices), we used the MA3T-MC to obtain preliminary results on the vehicle and mobility technology acceptance as shown in Figure III.2.2 and Figure III.2.3.



(a) without AV technology

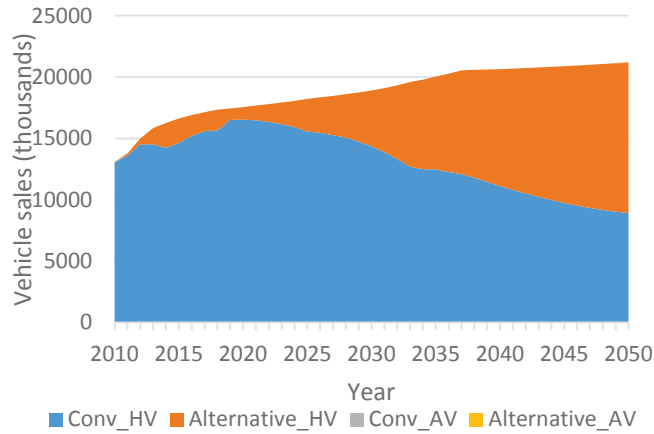


(b) with AV technology

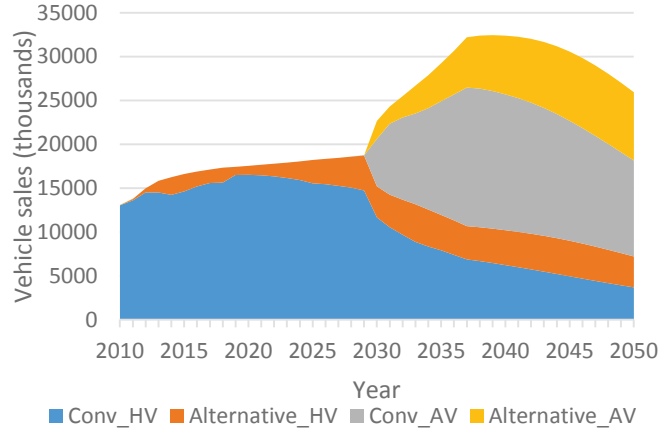
Figure III.2.2 Mobility choices in person miles traveled (PMT)

Figure III.2.2 shows the technology acceptances of different mobility choices. In particular, Figure III.2.2 (a) corresponds to the scenario when AV technology is assumed not available in the market in the simulation time scope (before 2050), while Figure III.2.2 (b) is associated with the scenario when AV technology is available in the market in 2030 and is getting mature since then. It is shown that, when AV technology is not considered (Figure III.2.2 (a)), the non-automated shared mobility gradually increases its acceptance among travelers with

the assumption that travel cost for shared mobility is continuously reduced over time. However, in all simulation years, driving personal vehicle is the primary transportation mode. On the other hand, when AV technology is considered (Figure III.2.2 (b)), the automated shared mobility is becoming a major transportation mode in later years, mainly thanks to its benefits on time and travel cost savings.



(a) without AV technology



(b) with AV technology

Figure III.2.3 Sales by vehicle technologies

Figure III.2.3 shows the estimated sales of different vehicle choices without AV technology (Figure III.2.3(a)) and with AV technology (Figure III.2.3 (b)). All vehicle technologies are grouped into four categories, conventional fuel HV (Conv_HV), alternative fuel HV (Alternative_HV), Conventional fuel AV (Conv_AV), and alternative fuel AV (alternative fuel AV). When AV technology is not considered (Figure III.2.3(a)), alternative fuel HVs including both plug-in hybrid electric vehicle (PHEVs) and battery electric vehicle (BEVs) gradually increase their sales and reach a total market share higher than 50% by 2050. When AV technology is

assumed to enter in the market in 2030 (Figure III.2.3(b)), the total sales are increased significantly shortly after 2030 mainly because of the AV technology. The total sales gradually declines in later years because more consumers choose to use other mobility choices as shown in Figure III.2.2(b).

Figure III.2.4 shows the probability of choice of vehicle fuel and mobility technologies by each of selected 8 of the modeled 7238 consumer segments. Each line represents the choice probability by a consumer segment for (a) buying new personal vehicles (including HV and AV), (b) primarily driving current vehicles, (c) primarily using public transit, (d) buying new personal AVs, (e) buying new battery electric AVs, (f) buying new battery electric HVs, (g) primarily using AV TNC, and (h) primarily using HV TNC.

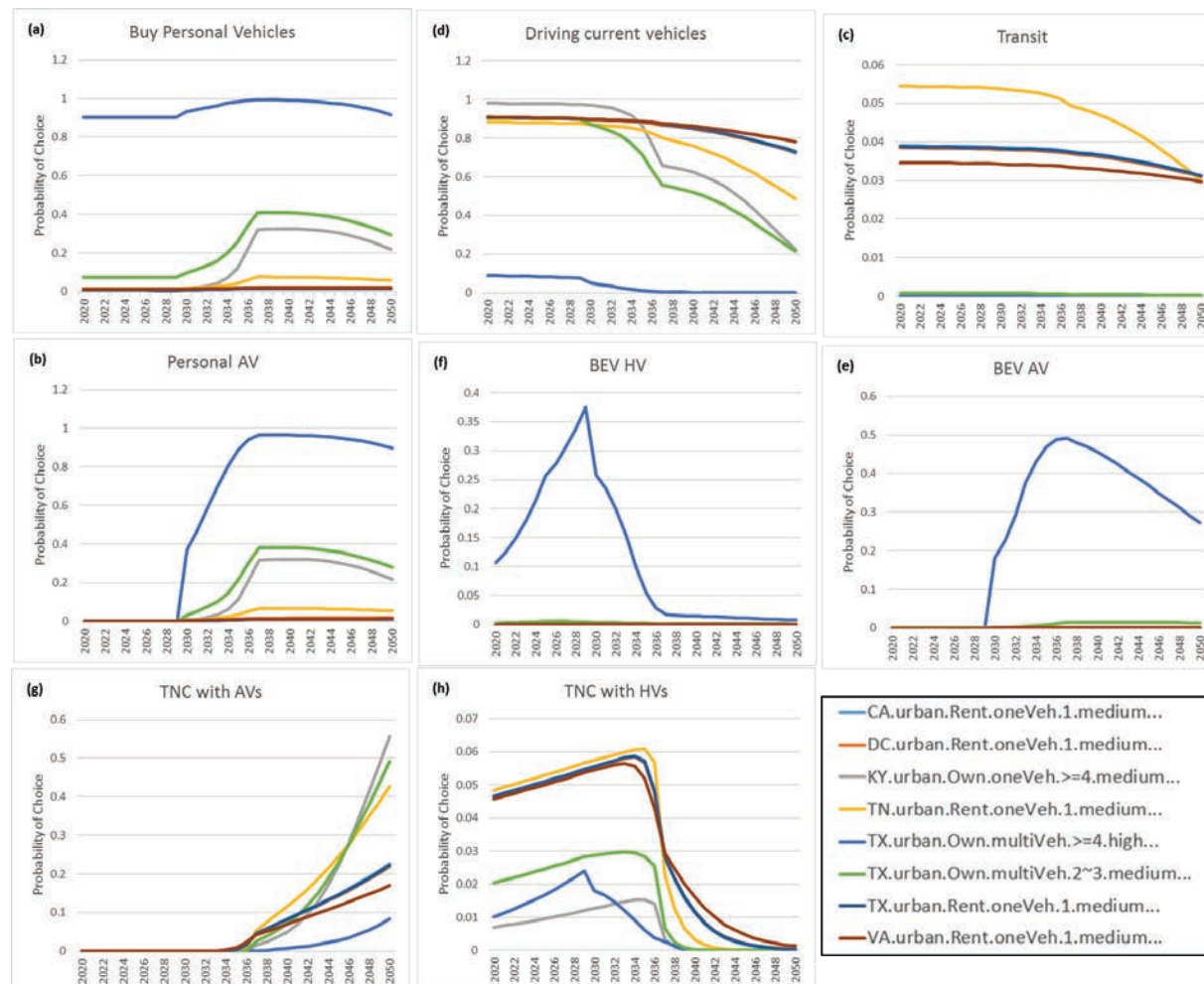


Figure III.2.4 Disaggregate Consumer Choices of Vehicle and Mobility Technologies

Conclusions

In FY18, we developed a segmentation method for clustering all NHTS sampled households into 7,238 segments to reflect heterogeneous travel behaviors. These heterogeneous travel behaviors are important factors to evaluate future technology acceptance of electrification, automation, and shared mobility in the transportation sector. We also completed the functional development of the MA3T-MC model, integrated with the segmentation results, and we showed a set of preliminary findings on the vehicle and mobility choices in both mid- and long term-scopes. We found that the AV technology can have a disruptive impact for both

shared mobility fleet and personal vehicles in the market mainly because of its consumer value on travel time cost recovery, driving stress reduction, and safety improvement.

For future work, the MA3T-MC model needs improved assumptions on both AV technology and shared mobility characteristics from other SMART tasks. Also, the MA3T-MC model could provide scenario results of technology acceptance of different vehicle and mobility choices to facility other SMART research. Another extension is to improve the modeling structure of the MA3T-MC model. For example, currently the vehicle sales and stock are assumed to have no impact on the average vehicle miles traveled (VMT) in the MA3T-MC model. However, when the sales are significantly increased after 2030 as shown in Figure III.2.3(b), that will lower the average VMT because each household has limited time budget in operating personal vehicles. That will in return limits the total sales of personal vehicles. This factor could be integrated in the MA3T-MC model.

Key Publications

1. Fei Xie, Zhenhong Lin, (2018). A Segmentation Method in Modeling Heterogeneous Mobility Behaviors using Travel Survey Data – a Case Study with the 2017 National Household Travel Survey (draft).

III.3 Mobility Behavioral Responses to Transportation Network Companies (NREL, LBNL) [Task 2.2]

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Start Date: May 2017

End Date: September 2019

Project Funding (FY18): \$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 analyzes the relationship between the supply of TNCs in a region and impacts on mobility and travel behavior (e.g. vehicle ownership, deadheading, VMT) and energy use. The results are useful as inputs for travel activity models used in other pillars (e.g. BEAM and POLARIS) to test the sensitivity of the availability of these services to travel and 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, vehicle type (e.g. fuel efficiency, electric vehicles) and vehicle miles of travel. This will help 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 several activities under this task in 2018:

- Examine the relationship between the entrance of TNC services across U.S. cities (first at the urban area level, and subsequently at the zip code level) and personal vehicle registrations.
- Travel and energy implications analysis of a database of individual rides provided by a TNC in Austin, Texas.
- Coordination with other SMART pillars to develop a TNC research framework identifying data and research needs to understand energy consequences of widespread use of TNC services.
- Begin analysis of effect of TNC entry on vehicle ownership and VMT in Texas, using dataset of individual vehicle odometer readings.

Approach

For the analysis of the relationship between date of entry of TNC service and vehicle registrations, we use the difference-in-difference econometric statistical regression model with 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: TNC entry dates (Month/Year) using UberX and Lyft.
- Controlling Variables: Population, population density, economic variables such as income and unemployment.

For the analysis on travel and energy implications of a TNC service in Austin, TX, we used a dataset of around 1.5 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 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 FY18 we drafted three research reports. Preliminary results from each of the reports are as follows:

Impacts of Ride-hailing on Vehicle Registrations

Preliminary results suggest that TNC entry has increased vehicle ownership and has an ambiguous effect on electric vehicle registrations. In all cases assessed, we show results for two different regression models with different representations of TNC service availability in an urban area or ZIP code: (1) an average effect based on whether TNC had launched in an area in a given year; and (2) a discrete annual effect that estimates TNC entry effect in each year after TNC entry. For each estimate reported, we also provide the 95% confidence interval (using cluster-robust standard errors) in parentheses.

We find that TNC entry is associated with an increase in per-capita vehicle registrations. At the urban area level, the average effect model suggests that, on average, TNCs increase per-capita vehicle registrations by 1.2% (95% confidence interval: 0.5% to 1.9%) over the period examined (relative to per-capita registration had the TNC not been introduced), and the discrete annual model finds an effect that generally agrees in magnitude with the binary model and that increases over time, from 1.4% (0.7% to 2.1%) in year one to 3.3% (1.7% to 4.9%) in year three. ZIP code-level results generally agree: the average effect model suggests that, on average, TNCs increase per-capita vehicle registrations by 1.2% (95% confidence interval: 0.9% to 1.4%) over the period examined (relative to per-capita registration had the TNC not been introduced), and the discrete annual model finds an effect that generally agrees in magnitude with the binary model and that increases over time, from 1.3% (1.1% to 1.5%) in year one to 2.2% (1.6% to 2.8%) in year three. Estimates for control variables exhibit expected signs: per-capita vehicle registrations increase with higher populations at a decreasing rate (positive linear effect and negative quadratic effect), decrease with higher population densities at an increasing rate (negative linear effect and negative quadratic effect), decrease with increases in unemployment, and increase with higher average income at a decreasing rate (positive linear effect and negative quadratic effect).

Travel and Energy Implications of a TNC service in Austin, TX

Using detailed data on approximately 1.5 million individual rides provided in the RideAustin program in Austin Texas, we quantify: the additional miles TNC drivers drive: before beginning and after ending their shifts, to reach a passenger once a ride has been requested, and between consecutive rides (all of which is referred to as deadheading); and the relative fuel efficiency of the vehicles that RideAustin drivers use compared to the average vehicle registered in Austin. We conservatively estimate that TNC driver commutes to and from their service areas account for 19% of total ride sourcing VMT; in addition, we estimate TNC drivers drove 55% more miles between ride requests within 60 minutes of each other, accounting for 25% of total ride sourcing VMT. Vehicles used for ride sourcing are on average two miles per gallon more fuel efficient than comparable light-duty vehicles registered in Austin, with twice as many hybrid-electric vehicles. New generation battery electric vehicle with 200 miles of range would be able to fulfill 90% of full-time drivers' shifts on a single charge. The RideAustin data also indicate that a substantial percentage of all rides start or end at downtown entertainment and airport land uses. We estimate that the net effect of ride sourcing on energy use is a 43% to 92% increase compared to baseline pre-TNC personal travel. Figure III.3.1 summarizes the net effect of five factors discussed above on the energy use from ride sourcing operation.

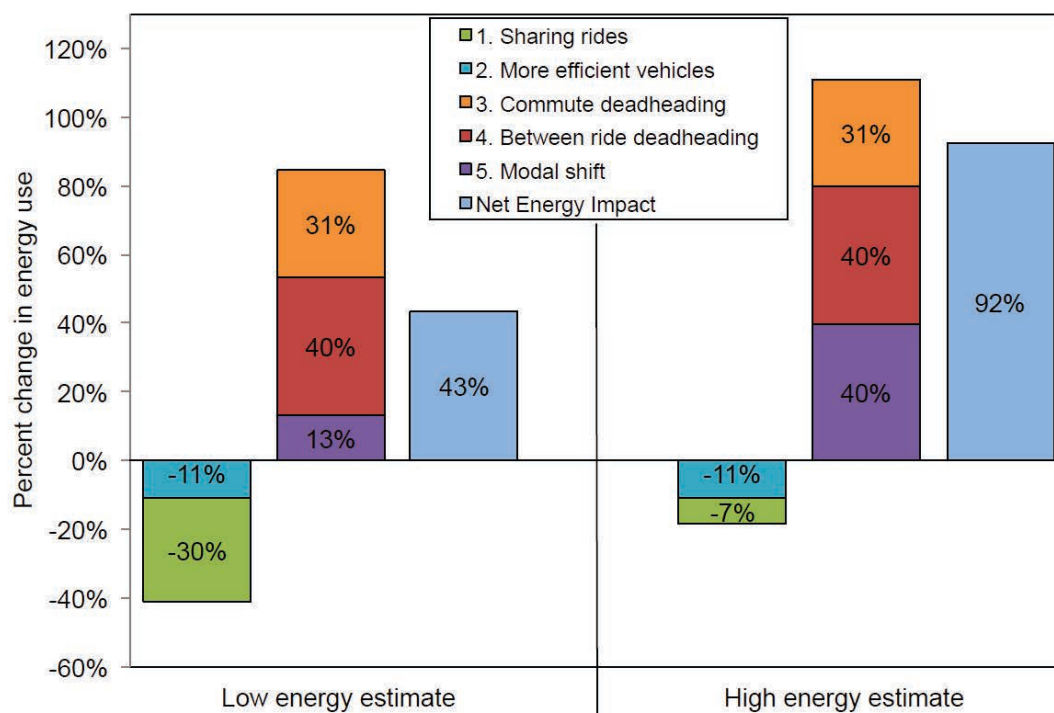


Figure III.3.1 Low and high estimates of net energy impact of ride sourcing in Austin

Quantifying the Impacts of TNCs on Transportation and Energy

TNCs impact transportation and energy across multiple domains such as vehicle miles traveled, parking, safety, and energy use. Furthermore, TNCs combined with traditional and emerging services represent the onset of mobility as a service (MaaS) in which transportation is ordered, purchased, and consumed as an integrated system, rather than as a small portion of a single monthly budget. MaaS is likely to impact not only the traveler and network, but also the built environment, future infrastructure (e.g. parking, curb utilization), fleet management, regulations, and key social, economic, and energy implications. Although TNCs have gained rapid popularity, data and research that can inform mobility and energy impacts remains scarce. There is a critical knowledge gap in analyzing the conditions that can drive various emerging mobility services towards societal goals. This project aims to address this gap by developing a framework to explore the energy

impacts of ride-hailing that span key research questions, hypotheses, data needs, and data collection strategies. The comprehensive framework proposed is intended to guide the future (re)design of integrated mobility systems, harnessing new technologies and services to help align public and private co-benefits, while also addressing critical potential risks and unintended consequences. The draft preliminary research framework to quantify energy impacts is presented as Table III.3.1.

Table III.3.1 TNC Energy Framework, Potential Impacts

ACTORS	TOPIC	SUB-TOPIC/RESEARCH QUESTIONS	POTENTIAL IMPACTS
<i>Suppliers (MaaS providers)</i>	Vehicle Fleet	Are vehicle fleets (including EVs) more fuel efficient?	+
	Operations & Style	Location of vehicles and driving behavior (e.g., smoothed acceleration/deacceleration)	+
	Supply & Demand	Number of vehicles in the fleet per MaaS demand	+ -
	Deadheading & Idling	Deadheading & idling (i.e., no passenger, zero occupancy vehicles)	-
<i>Consumers (MaaS users)</i>	Mobility Behavior Changes	Mode replacement and modality style changes	+ -
		Vehicle ownership reduction	+ -
		Increase true ridesharing (i.e., pooling with strangers)	+
		Induced travel (increases energy and mobility)	-
		Relocation: residence, travel	+ -
<i>Institutions (Cities)</i>	Infrastructure, Standards & Regulations	Support of automated, electric/efficient, and sharing transportation; parking reduction, increases in density, multi-modal infrastructure	+

Conclusions

All the studies under this task are ongoing; no conclusions are available as of this time.

Key Publications

1. Wenzel, T., Rames, C., Kontou, E., Henao, A. *Travel and Energy Implications of Ridesourcing Services in Austin, Texas*. Transportation Research Part D: Transport and Environment. In review.

III.4 Mobility Behavior and System Energy Efficiency: Plug-in Electric Vehicle Benefits Analysis (LBNL) [Task 3.1]

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Start Date: October, 2016	End Date: September, 2019	
Project Funding (FY18): \$1,475,000	DOE share: \$1,475,000	Non-DOE share: \$0

Project Introduction

As new mobility options and new vehicle technologies disrupt the transportation system, there remains a high degree of uncertainty around the interaction between these trends and the behaviors and preferences of travelers. This project seeks to quantify the energy and mobility impacts of these trends by simulating in detail the emerging transportation system and the heterogeneous preference profiles of travelers based on empirical studies of traveler behavior.

We approach this task in two phases: 1) We developed the BEAM travel demand model, which is capable of simulating a multi-modal transportation system including the operations of demand-responsive ride hailing fleets. The model was applied and calibrated to the San Francisco Bay Area. 2) We explored the modal sensitivity of travelers, the impact of their value of time, and the limits of technology adoption based on results from the Whole Traveler Behavioral Study.

The following progress report summarizes the BEAM model, describes the study design, and explores results from the model application.

Objectives

Our project objective is to quantify the energy and mobility impacts of these trends by simulating in detail the emerging transportation system and the heterogeneous preference profiles of travelers based on empirical studies of traveler behavior.

Approach

The BEAM Model

The Behavior, Energy, Autonomy, and Mobility (BEAM) model is an integrated, agent-based travel demand simulation framework. Individual agents express preferences through a utility-maximizing evolutionary algorithm that minimizes each individual's cost and time spent traveling via diverse modal options, including the competition for scarce supply resources such as parking spaces and charging infrastructure.

BEAM simulates the essential elements that compose a dynamic transportation system. From the road network, parking and charging infrastructure, to the transit system and a synthetic population with plans and preferences, the virtual system is an amalgamation of multiple spatially resolved layers that together represent an integrated transportation system (Figure III.4.1).

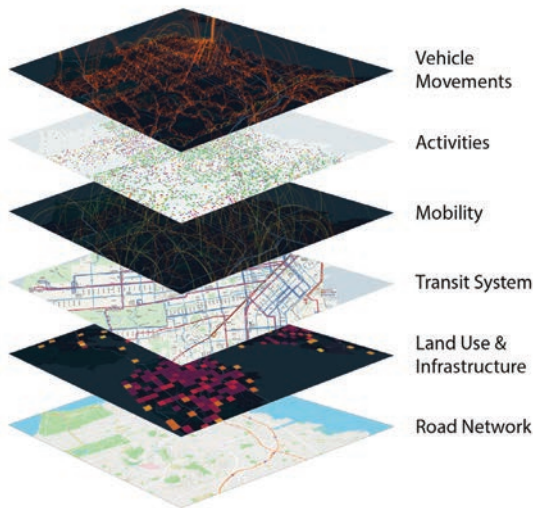


Figure III.4.1 BEAM represents the road network, land use, parking infrastructure, charging infrastructure, transit system, traveler activities, personal mobility, and explicit vehicle movements.

BEAM is an extension to the MATSim (Multi-Agent Transportation Simulation) model, where agents employ reinforcement learning across successive simulated days to maximize their personal utility through plan mutation (exploration) and selecting between previously executed plans (exploitation). The BEAM model shifts some of the behavioral emphasis in MATSim from across-day planning to within-day planning, where agents dynamically respond to the state of the system during the mobility simulation. In BEAM, agents can plan across all major modes of travel including driving, walking, biking, transit, and demand-responsive ride hailing. Several key features of BEAM are summarized here:

MATSim Integration - BEAM leverages the MATSim modeling framework [1], an open source simulation tool with a vibrant community of global developers and users. MATSim is extensible (BEAM is one of those extensions) which allows modelers to utilize a large suite of tools and plug-ins to serve their research and analytical interests.

Resource Markets - While BEAM can be used as a tool for modeling and analyzing the detailed operations of a transportation system, it is designed primarily as an approach to modeling resource markets in the transportation sector. The transportation system is composed of several sets of mobility resources that are in limited supply (e.g. road capacities, vehicle seating, TNC fleet availability, refueling infrastructure). By adopting the MATSim utility maximization approach to achieving user equilibrium for traffic modeling, BEAM is able to find the corresponding equilibrium point across all resource markets of interest.

Dynamic Within-Day Planning - Because BEAM places a heavy emphasis on within-day planning, it is possible to simulate modern mobility services in a manner that reflects the emerging transportation system. For example, a virtual ride hail service in BEAM responds to customer inquiries by reporting the wait time for a ride, which the BEAM agents consider in their decision on what service or mode to use.

Rich Modal Choice – BEAM offers multiple mode choice specifications. Mode can be exogenously defined, or agents can endogenously choose mode during the simulation day at the trip level (dynamic mode choice) or before the simulation at the tour level (tour-based modal replanning). The modal options available to agents include walk, bike, drive alone, ride hail, and three different variations on public transit (walk to transit, drive to transit, and take ride hail to/from transit).

Ride Hail Operations – Ride hailing companies are already changing the mobility landscape and as driverless vehicles come online, the economics of these services will improve substantially. In BEAM, ride hailing is modeled as a fleet of taxis controlled by a centralized manager that responds to requests from customers and dispatches vehicles accordingly.

Designed for Scale - BEAM is written primarily in Scala and leverages the Akka_ library for currency which implements the Actor Model of Computation [2]. This approach simplifies the process of deploying transportation simulations at full scale and utilizing high performance computing resources. BEAM has been designed to integrate with Amazon Web Services including a framework to automatically deploy simulation runs to the cloud.

Traveler Heterogeneity

In BEAM, preference heterogeneity is primarily expressed through the value of travel time of each traveler (

Figure III.4.2). Based on research conducted by the SFCTA [3], we distributed the value of time lognormally with a mean value conditioned on household income. In addition, personal and household characteristics such as gender, age, household size, number of personal vehicles, and any other readily available co-variate from the American Community Survey are available used to inform agent choices within BEAM.

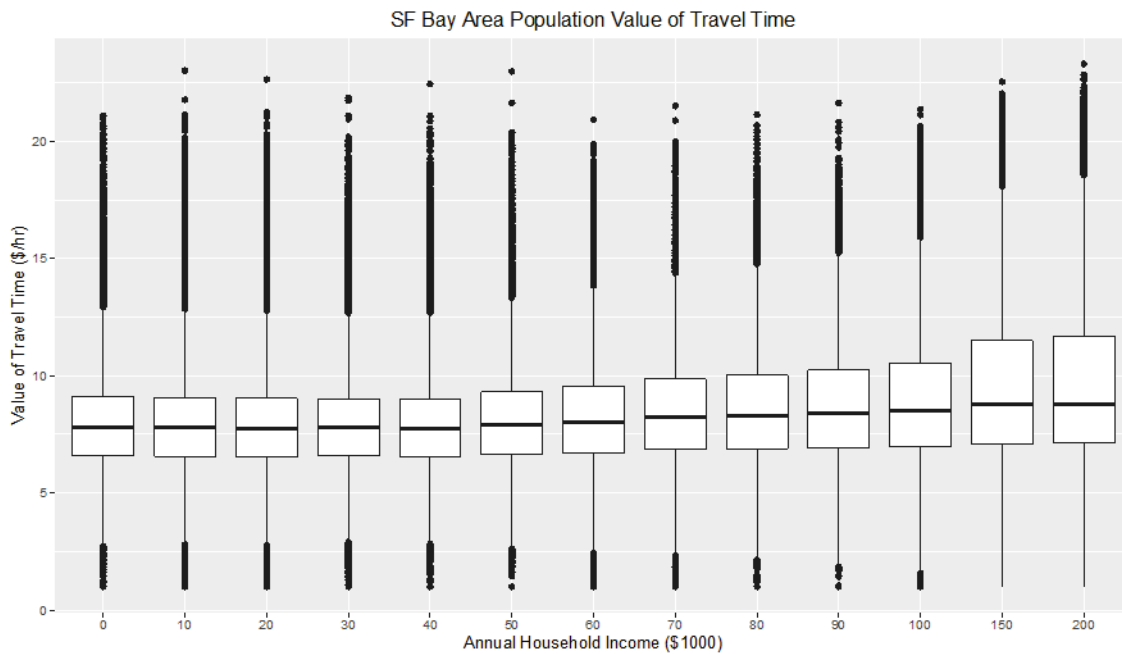


Figure III.4.2 Value of travel time in the virtual population simulated in BEAM, disaggregated by annual household income (note that “200” in the figure contains all income above \$200k).

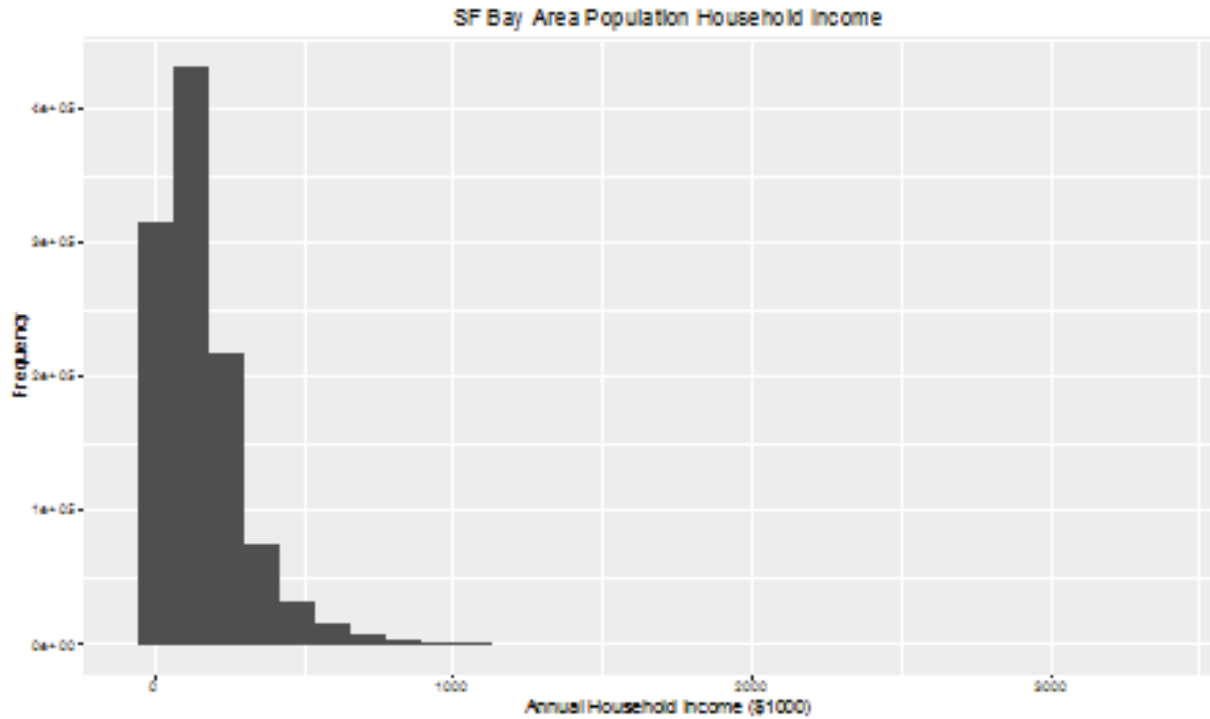


Figure III.4.3 Household income distribution of the simulated population in BEAM.

Technology Diffusion Scenarios

In order to explore the potential impacts of shared, automated mobility service adoption, we created three scenarios based on results from the Whole Traveler Behavioral Study [4]. Each scenario is distinguished by the number of simulated travelers who include ride hail or ride hail transit as modal alternatives in their mode choice procedure.

Table III.4.1 Technology diffusion scenarios used for analysis.

Scenario	Description	Rationale
Unlimited	This is equivalent to the base scenario used for calibration, but it features a price for ride hail services 50% of the base scenario.	Serves as a base scenario that assumes no one will categorically refused to adopt AVs in the future. 100% of the population considers ride hail as a mode in this scenario.
AV-Interested	Based on Whole Traveler respondents who expressed interest in adopting AV technology when available.	Serves as a more conservative scenario based on the limits of expressed interest in AV technology. In total, 47% of the population considers ride hail as a mode in this scenario.
RH-Interested	Based on Whole Traveler respondents who either use ride hail or are interested in using ride hail.	Serves the most conservative scenario due to a modified application of parameters from whole traveler (without county fixed effects). In total, only 26% of the population consider ride hail as a mode in this scenario.

Results

We investigate the medium-term impact of behavioral sensitivity to mode through sensitivity analysis. Using a calibrated model with heterogeneous values of time, we assess the response of the travelers to changes in cost of each mode. In Figure II.4.4 and Figure II.4.5, we see that changes to the cost of gasoline (+/- 50%), the cost of ride hailing (+/-25%), and the cost of transit (+/-50%) can yield substantial shifts in modal share and substantial changes in system energy consumption, as much as 18%.

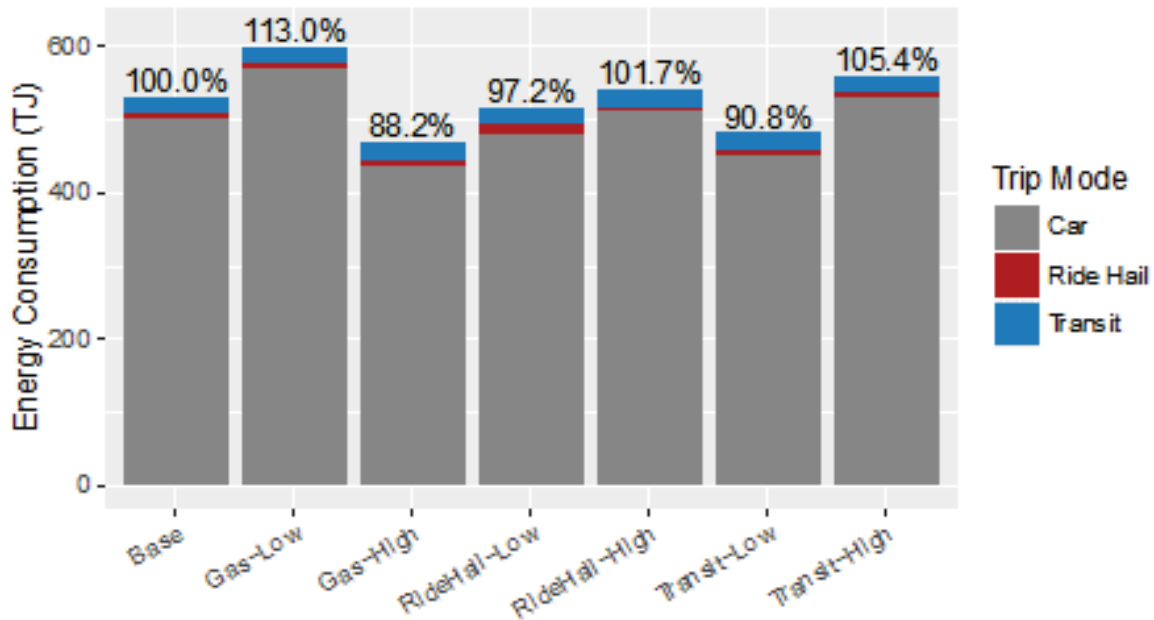


Figure III.4.4 Modal shares for the Base San Francisco Bay Area scenario and three sets of variations with cost of modes shifted +/-50% (for gasoline and transit) or +/-25% (for ride hail).

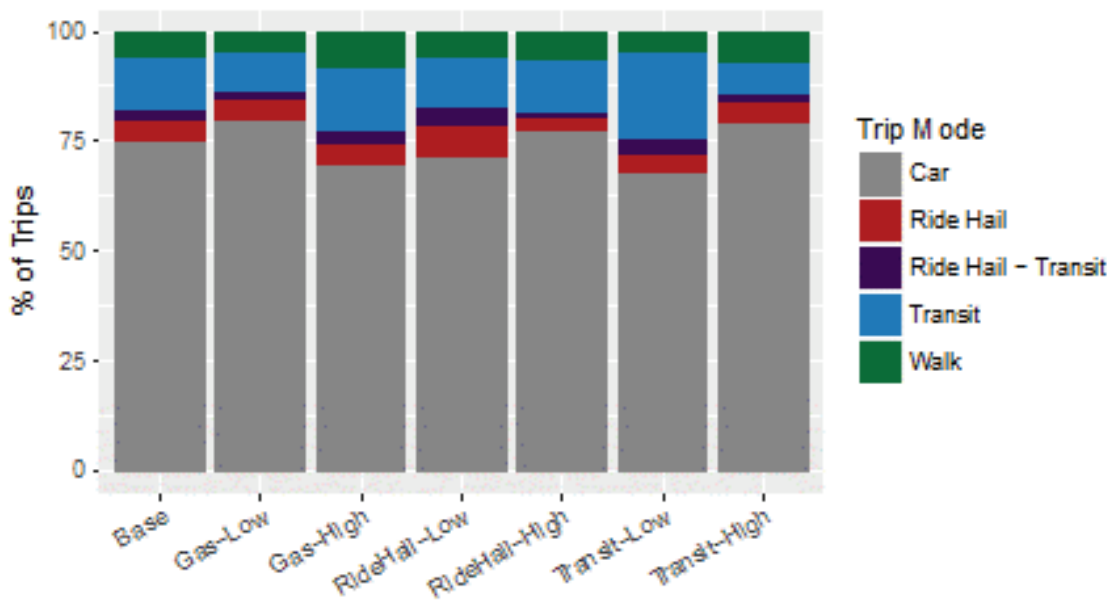


Figure III.4.5 System energy consumption for the Base San Francisco Bay Area scenario and three sets of variations with cost of modes shifted +/-50% (for gasoline and transit) or +/-25% (for ride hail). Percentage labels are all relative to the Base scenario.

When the SF Bay Area scenario is simulated across the three scenarios defined in Table III.4.1, the restrictions

on ride hailing and ride hail transit as modes result in substantial shifts in modal share from these modes to other modes, mostly car (Figure III.4.6). Even though ride hail trips produce more vehicle miles traveled than car (due to empty vehicle movements), we find that scenarios with reduced ride hail use lead to increases in energy consumption (Figure III.4.7). This is due to a reduction in ride hail transit as a mode and a slight reduction in walking.

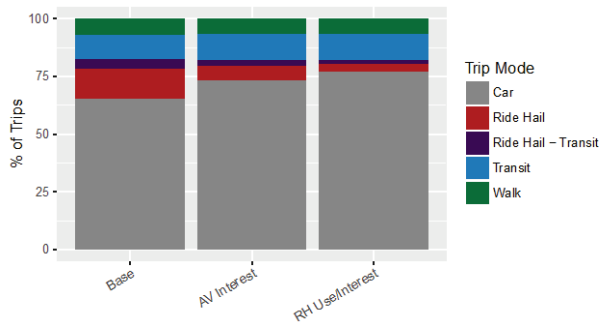


Figure III.4.6 Modal share between a base scenario (equivalent to the scenario used for calibration except with reduced ride hail cost by 50%) and two scenarios where adoption of ride hail is limited according to the demographic distributions estimated from the Whole Traveler Behavioral Study. The AV Interest scenario simulates adoption by respondents who indicated interest with AV technology. The RH Use/Interest scenario includes respondents who indicated use of or interest in shared mobility (but with overall reduced uptake due to a lack of geographic specificity in application of the model results).

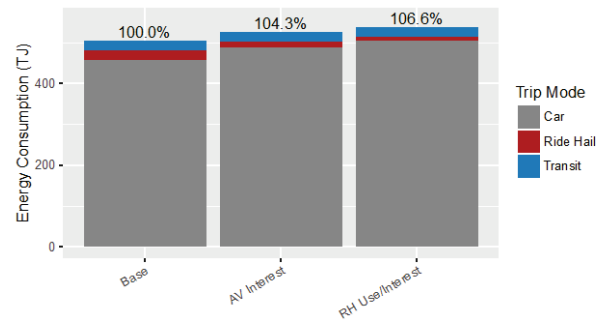


Figure III.4.7 Total system energy consumption comparison between a base scenario (equivalent to the scenario used for calibration except with reduced ride hail cost by 50%) and two scenarios where adoption of ride hail is limited according to the demographic distributions estimated from the Whole Traveler Behavioral Study. The AV Interest scenario simulates adoption by respondents who indicated interest with AV technology. The RH Use/Interest scenario includes respondents who indicated use of or interest in shared mobility (but with overall reduced uptake due to a lack of geographic specificity in application of the model results).

Conclusions

We have introduced the BEAM travel demand model and our application to the San Francisco Bay Area. We have conducted an initial set of calibration and validation exercises. We have conducted a series of sensitivity studies with a focus on the impact of traveler behavior on modal shares and system energy consumption.

- The population is sensitive to modal cost, varying costs by +/-50% can increase the energy consumption of the system as much as 13% or decrease by as much as 18%.
- The diffusion potential of AV technology in the context of automated ride hailing will result in different modal and energy outcomes. When substantial numbers of travelers are uninterested in using an automated ride hailing fleet, the modal shares involve more driving due to the reduction in use of ride hail as a transit access/egress mode. This increases system energy consumption as much as 6%.

Key Publications

1. Colin Sheppard, Rashid Waraich, Sid Feygin, Michael Zilske, Anand Gopal. “SMART Mobility MDS Task 3.1 - BEAM Interim Report on Calibration Results, Medium-term Study, and Proof-of-Concept Long-term Approach.”

References

1. “The MATSim Book,” *MATSim.org*. [Online]. Available: <https://matsim.org/the-book>. [Accessed: 30-Sep-2018].

2. G. A. Agha, “Actors: A Model of Concurrent Computation in Distributed Systems.,” MASSACHUSETTS INST OF TECH CAMBRIDGE ARTIFICIAL INTELLIGENCE LAB, MASSACHUSETTS INST OF TECH CAMBRIDGE ARTIFICIAL INTELLIGENCE LAB, AI-TR-844, Jun. 1985.
3. “Modeling and Travel Forecasting | San Francisco County Transportation Authority.” [Online]. Available: <https://www.sfcta.org/modeling-and-travel-forecasting#doc>. [Accessed: 30-Sep-2018].
4. A. Spurlock *et al.*, “How to reach the users: Evaluating what characteristics indicate adoption of energy efficient transportation solutions in the face of rapid transformation,” *Peer Rev.*, 2018.

Acknowledgements

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III.5 Travel Behavior Simulation Modeling – POLARIS [Task 3.2]

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Project Funding (FY18): \$375,000	DOE share: \$375,000	Non-DOE share: \$0

Project Introduction

The research in transportation clearly indicates that potential changes in travel demand are a key driver of uncertainty surrounding the overall impacts of future mobility on energy use. In this task, we seek to extend POLARIS to better characterize mobility decisions that are made under new mobility technologies and modes. We will enhance core behavioral modeling components of POLARIS 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).
- Model traveler behavior in POLARIS as it pertains to vehicle choice, activity planning, mode choice, and other choices that are sensitive to factors related to future mobility scenarios.
- Understand technological, behavior, and other factors that affect shifts in mobility energy productivity.
- Evaluate behavioral response due to future mobility, design policies, and model energy impacts.
- Complement other approaches by testing in multiple regions, using multiple approaches, and modelling different behaviors.

Approach

The approach to achieving the objectives of this project involves implementing various behavioral models developed as part of this research, other MDS tasks, or drawn from the literature. 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 MDS scenarios. Figure III.5.1 overviews the improvements to the core POLARIS simulator. The primary tasks under the travel-behavior simulation project over the last fiscal year involved:

1. Development of an activity time of day and duration choice model,
2. Updating the existing mode choice model to capture multimodal travel,

3. Estimation of a new scheduling and conflict-resolution model,
4. Implement an intra-household automated vehicle sharing optimization model,
5. Exploring the behavioral sensitivity of the POLARIS ABM with the above improvements, and
6. Case studies demonstrating energy impacts under various scenarios.

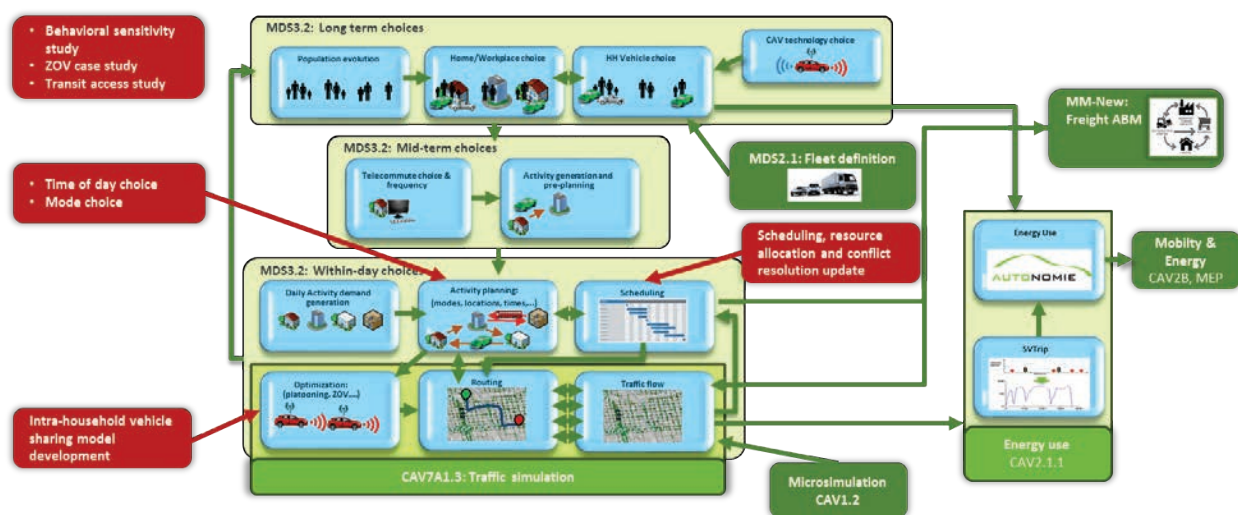


Figure III.5.1 POLARIS modeling process with MDS improvements highlighted

The project requires significant inputs from throughout the SMART Mobility research program, and collaboration with a number of other laboratories and universities. The University of Illinois at Chicago (UIC) helped estimate the activity start and duration model, as well as developing a new activity scheduling and conflict resolution model. The University of New South Wales (UNSW) and UIC contributed to the update of the mode choice model and exploration of value of travel-time changes through the FY 2017 MDS 2.1 task. All models, whether estimated at Argonne, estimated through university or laboratory collaborators, or drawn from the literature, were implemented in POLARIS as agent-based behavioral modules controllable through external parameter files, as described in the POLARIS repository and various publications. We then used the POLARIS-Autonomie simulator with updated behavioral modules to analyze the energy impacts for scenarios related to level 5, fully automated vehicle sharing, as discussed in the CAV7A1.3 annual report, and for intermodal transit access improvement, as detailed in the MM1.3 annual report.

Activity time of day and duration modeling

Argonne and the team from UIC developed a complex econometric formulation relating activity start time and duration choice to a variety of activity-specific characteristics, individual socio-demographics, scheduling, and system performance variables. The model was implemented as a copula model between a hybrid random-regret minimization and utility maximization choice model (for start time choice) and a hazard-duration model for the duration of the activities. This formulation allows heterogeneous choices to be represented and the significant correlations to be captured between the choice of activity start time-of-day (TOD) and activity duration (Golshani et al. 2018). The model was coded into the POLARIS framework. It was then calibrated using simulation to update the time-specific constants. Key findings of the model are demonstrated by the direct and cross elasticities of the start time alternatives, as shown in Figure III.5.2. The model is critically important, because it allows the simulation to capture the process for time-of-day choices and how these choices change under different network performance and generalized cost assumptions. This makes the model sensitive and

dynamically responsive to changes in congestion, reliability, valuations of travel time, and other factors. The model’s sensitivity to key covariates was evaluated and verified in the sensitivity study discussed below.

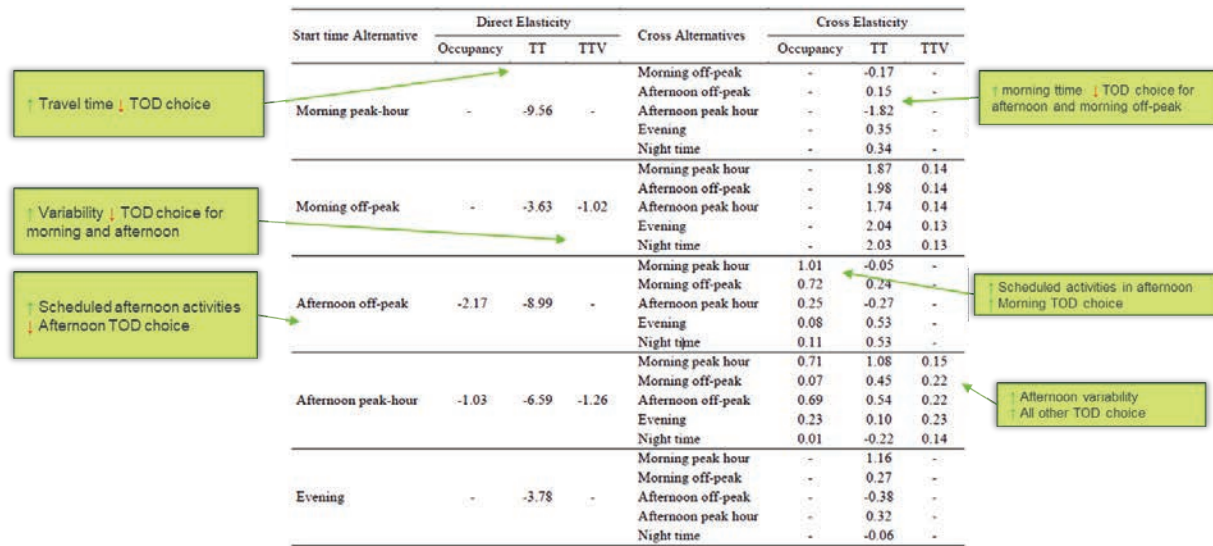


Figure III.5.2 Key findings from activity start time choice model

Mode choice modeling

We updated and improved the POLARIS base-mode choice so it can capture multi-modal decision-making and incorporate new mobility options. The model estimation process leveraged multiple datasets, including the Chicago 2009 household travel survey, as well as a recent survey of Chicago-area transit riders (Auld et al. 2019). Multiple surveys were combined to both capture the baseline mode choice, and understand how mode choices have changed now that new mobility options are widely available that were not when the original Chicago household travel survey was completed. We developed a process to combine the datasets into a single dataset and impute characteristics of the non-observed mode alternatives using the POLARIS multi-modal router (see MM1.3 annual report for router details). The router allowed us to calculate exact travel cost/time components for various drive, transit, and intermodal options that we then used in model estimation. We also collected information on historical and current transit, taxi, and other modal fares, pass usage, parking costs, and so forth to enhance the realism of the estimated model. We then estimated separate and combined mode choice models for each dataset, for multiple trip types (i.e., home-based work/school, home-based other, non-home based). We analyzed results in terms of the reasonableness of the estimated value-of-travel time components; all models demonstrated good fit and expected behavior. Table I.5.1 shows value of time estimates for the home-based work model. In order to implement the model in a simulation, we made extensive changes to the POLARIS network skimming process, which generates average travel time and cost estimates from/to each zone in the model. The skimmed values are then used for each mode choice decision when the model is run. We updated the skimmer to include time-dependent skims by mode for all of the cost components required, including in-vehicle time access/egress time by car and walk, wait time, transfers, and fares paid.

Table I.5.1 Home-based Value of Time by Income Level

Mode	travel component	VOT by HH Income (\$)			
		5000	30000	75000	120000
Drive	time in motion	\$15.36	\$18.59	\$20.24	\$21.09
Drive	parking "vot"	\$66.66	\$80.68	\$87.85	\$91.53
Taxi	time in motion	\$59.37	\$71.86	\$78.25	\$81.53
RailDrv	IVTT + Ac/Eg	\$3.27	\$3.96	\$4.31	\$4.49
RailDrv	Waiting time	\$5.04	\$6.10	\$6.64	\$6.92
RailWlk	IVTT + Ac/Eg	\$2.53	\$3.06	\$3.33	\$3.47
RailWlk	Waiting time	\$3.99	\$4.83	\$5.26	\$5.48
XitDrv	total time (IV,Ac/Eg,Wait)	\$1.70	\$2.06	\$2.25	\$2.34
XitWlk	IVTT + Ac/Eg	\$11.04	\$13.36	\$14.55	\$15.16
XitWlk	Waiting time	\$9.16	\$11.08	\$12.07	\$12.57

Behavioral sensitivity analysis

We performed a behavioral sensitivity analysis on the updated POLARIS activity-based model to determine the simulator’s sensitivity to key behavioral parameters. A previous study revealed that miles traveled are sensitive to the travel time parameter in the mode and destination choice models, with an elasticity of approximately -0.25 (there is a 2.5% reduction in miles traveled for every 10% increase in the travel time parameters). We performed a new parametric study on 10 additional bundles of key behaviors to **identify key parameters for additional study to reveal how they will change under future mobility** scenarios. Figure III.5.3 shows the results of the analysis for the VMT metric. Key findings from this study include the sensitivity of regional mobility results to modal travel time components. Many other behavioral parameters were found to have limited behavioral impacts, likely due to the limited study area. Bloomington, Illinois, is relatively small, with poor transit service and homogenous land use mix. These factors all limit behavior responses, and require larger-scale analysis to identify further sensitivities.

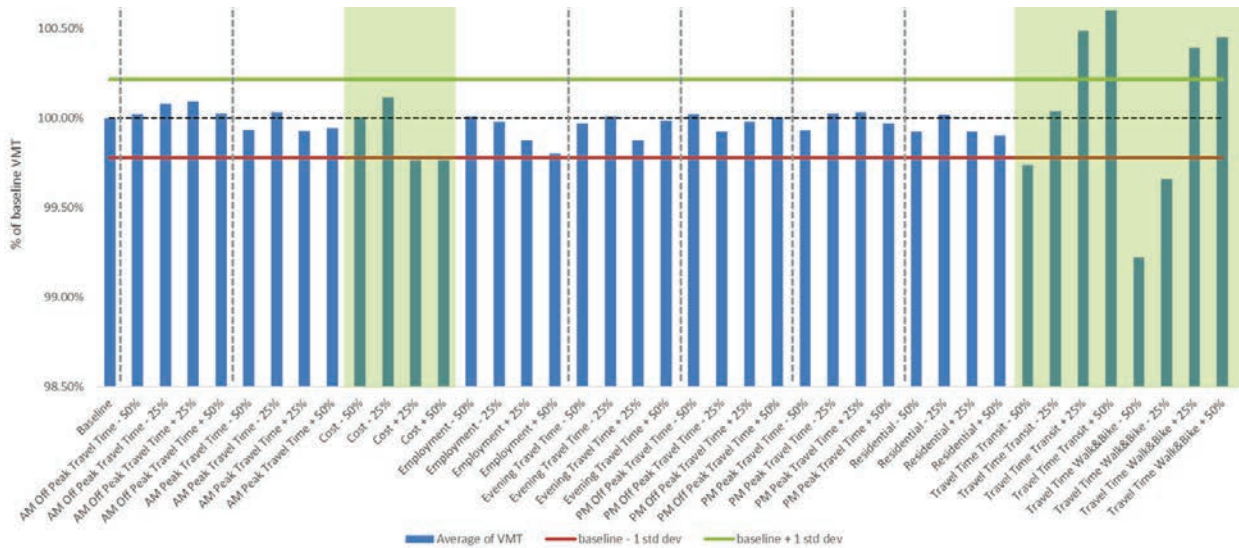


Figure III.5.3 VMT sensitivity to changes in behavioral parameters

Transit access study results

We performed a scenario analysis to explore the impacts of improving transit accessibility using the updated POLARIS model, including the new mode choice model and network skimmer along with the improved multi-modal router and transit simulator developed under MM1.3. This analysis was performed using the Bloomington, Illinois, model a representative small city with relatively limited transit service, where the majority of trips taken are by private automobile. The scenario analysis included a baseline scenario, as well as a scenario where transit access/egress by transportation network companies (TNCs) was subsidized by the transit agency at no cost to the traveler (a first-mile/last-mile TNC application). Table-III.5.2 shows the results of the scenario analysis.

Table-III.5.2 Transit Access Scenario Mobility and Energy Results

	Total VMT	SOV VMT	Taxi/TNC VMT	TNC-to-transit VMT	Bus VMT	SOV / Taxi/TNC %	Walk to Transit %	TNC to Transit %	Overall Transit %
Baseline	2,265,786	1,946,530	313,974	1,805	3,477	72.6%	1.3%	0.1%	1.3%
TNC access	2,232,961	1,945,728	278,018	5,737	3,477	72.4%	1.2%	0.3%	1.5%
% change	-1.4%	0.0%	-11.5%	217.8%	0.0%	-0.3%	-6.3%	226.6%	10.9%

The simulation results demonstrate a moderate reduction in auto-based VMT from single-occupant, high-occupancy, and taxi/TNC trips and a commensurate increase in transit use. This increases transit energy usage, but reduces overall energy use substantially because the transit modes tend to be much more efficient on a per-passenger basis. Interestingly, the 11% increase in overall transit use comes at an agency cost of subsidizing only 5,737 miles of TNC access for approximately 2,000 new transit riders. Most significantly, by providing these miles of TNC access, over 33,000 auto miles traveled are removed from the network, which also decreases overall system congestion. Figure III.5.4 shows the geographic distribution of where transit is used and the change in transit utilization under the TNC access scenario.

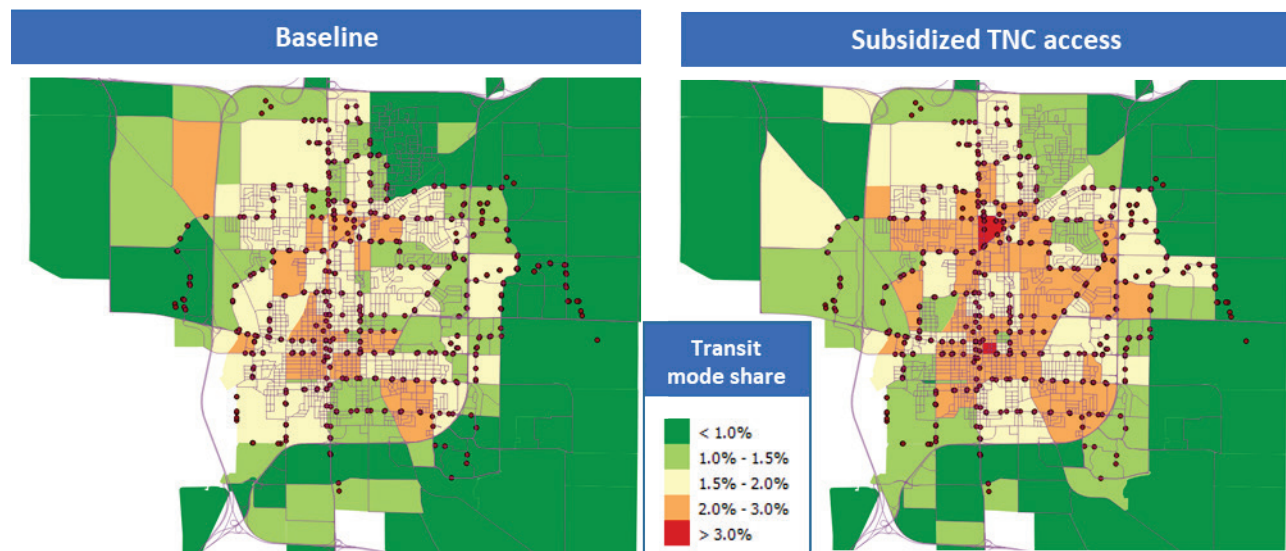


Figure III.5.4 Change in transit mode share from baseline to subsidized TNC access scenario

Overall, it appears that providing no-cost access to transit can increase overall transit ridership by increasing the catchment area of transit routes that are competitive with the auto mode. This extends potential transit use to riders outside of walking distance from the nearest stop. In addition, this also increases transit use by locking in the additional riders to the transit mode when they are in the downtown/business areas away from their vehicles.

Conclusions

We significantly enhanced POLARIS to simulate the impacts of various traveler behaviors under different future mobility scenarios. We implemented and tested key improvements to the mode choice and timing choice models, paired with improvements in the network skimmer and activity scheduler for more realistic activity pattern generation and choice specification, which demonstrate the sensitivity of the regional mobility metrics to the key parameters. The updated model has been used to explore potential impacts of transit access policies; increased drive-to-transit access demonstrates an increase in transit usage and reduction in energy usage and system congestion.

Key Publications

1. Ö. Verbas, J. Auld, H. Ley, R. Weimer, S. Driscoll (2018). A Time-Dependent Intermodal A* Algorithm: Methodology and Implementation on a Large-Scale Network, *Transportation Research Record: Journal of the Transportation Research Board* (Forthcoming).
2. R. Shabanpour, N. Golshani, M Tayaran, J. Auld, A. Mohammadian (2018). Analysis of telecommuting behavior and impacts on travel demand and the environment. *Transportation Research, Part D: Transport and Environment* (Forthcoming)

3. N. Golshani, R. Shabanpour, J. Auld, A. Mohammadian (2018), Activity start time and duration: incorporating regret theory into joint discrete–continuous models. *Transportmetrica A: Transport Science*, Taylor & Francis.
4. A. Shamshiripour, R. Shabanpour, N. Golshani, J. Auld, A. Mohammadian (2019). A flexible activity scheduling conflict resolution framework. Accepted for presentation at Transportation Research Board 99th Annual Meeting, Washington, DC, 2019.
5. M. Javanmardi, J. Auld, K. Gurumurthy (2019). Intra-Household Fully Automated Vehicles Assignment Problem Model Development and Case Study, Accepted for presentation at Transportation Research Board 99th Annual Meeting, Washington, DC, 2019.

IV SMART Mobility - Multimodal Transportation (MM)

IV.1 Enhance Existing Models to Estimate Impact of Modal Shifts; Intracity Passenger Travel (ANL) [Task 1.3]

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Start Date: October 1, 2017

End Date: September 30, 2018

Total Project Cost: \$200,000

DOE share: \$200,000

Non-DOE share: \$0

Project Introduction

With the advent of automated and connected transportation systems, car and bike sharing, transportation network companies (TNCs), and on-demand transit services, as well as the increasing availability of real-time traffic and transit information, travelers have the opportunity to evaluate their multiple routing options and make better-informed decisions. These advancements call for a comprehensive modeling of the system as an integrated multimodal network. The significance of having such an integrated tool lies in (1) a more accurate modeling of private car, transit vehicle, and traveler movements and interactions in an environment with various possible levels of connectedness and automation; and (2) a more accurate modeling of user decision making via integrated mode choice/path assignment and ensuring that the modeled choices are consistent with observation.

In this task, we sought to extend the POLARIS model to include multimodal network representation, intermodal routing, multimodal supply simulation of cars, transit (bus, urban rail, commuter rail, etc.), taxis and TNCs, and active modes (walking, biking, bike-sharing, etc.). This approach will enable us to model the supply aspect of intermodal transportation, which consists of complex interactions between cars, transit vehicles, and travelers. Moreover, we will extend the SVTriP model to generate realistic bus speed/acceleration/idling profiles to provide the necessary linkage between POLARIS and Autonomie. With these enhancements, we will be able to quantify the mobility and energy impact(s) of transit use under different scenarios in the context of the Chicago metropolitan region in Illinois, as well as in Bloomington, Illinois.

Objectives

- Quantify the energy impact of transit under different scenarios (ridership, vehicle technologies, etc.).
- Integrate the Autonomie energy models with POLARIS and quantify the energy impact(s) of transit under different scenarios using multi-year Chicago data.
- Extend SVTriP for transit buses.
- Extend POLARIS to simulate movements of multiple modes; simulation will account for traffic congestion, sit/stand/miss/get rejected for passengers, wait times, etc.

- Quantify the energy impact(s) of different transit ridership levels based on historical data and the use of TNC services as a competing or complementing mode.

Approach

The approach to achieving these objectives involves implementing various supply models and integrating them with the existing models in POLARIS. Figure IV.1.1 highlights the various components of POLARIS, as well as SVTriP and Autonomie, which have been relevant to this task.

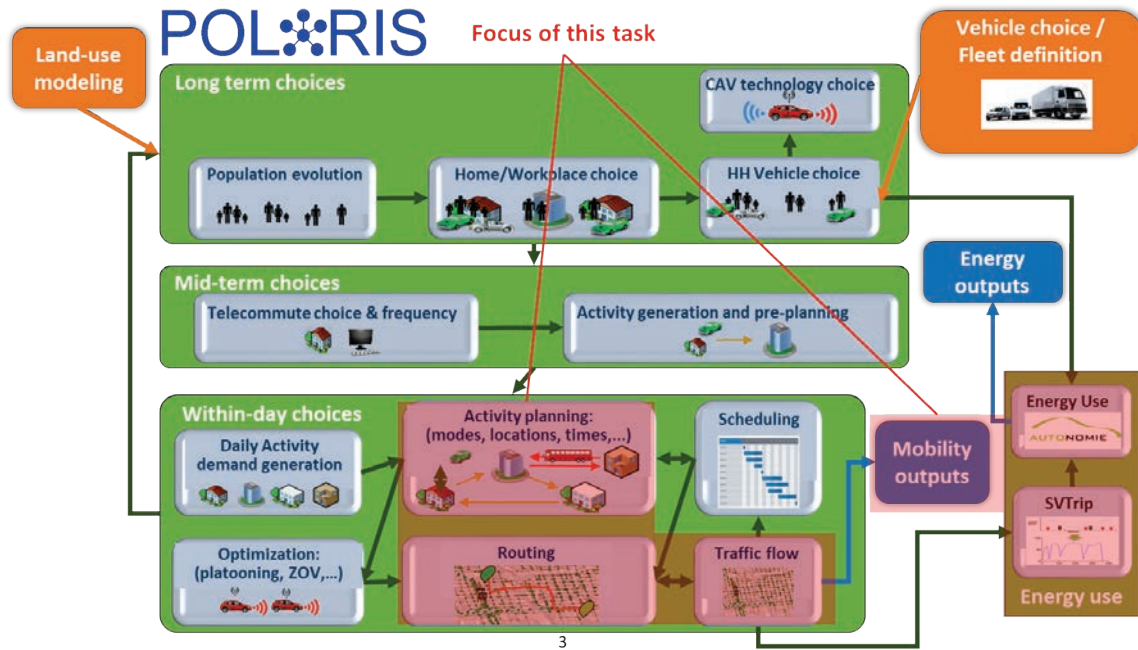


Figure IV.1.1 POLARIS Modeling Process with Multimodal Tasks Highlighted

The primary subtasks under this task over the last fiscal year involved the following:

6. Integrating the intermodal routing algorithm with the mode choice model of POLARIS.
7. Implementing complex transit fare structures to inform routing and mode choice.
8. Developing a multimodal simulator and integrating it into POLARIS.
9. Extending SVTriP for transit buses.
10. Running scenarios to test the impact(s) of transit use on mobility and energy.

Intermodal Routing Algorithm and Mode-Choice Integration

In FY 2017, a significant update to the POLARIS routing module was implemented allowing for heterogeneous, intermodal route selection. The newly developed, time-dependent intermodal A* (TDIMA*) algorithm is a point-to-point, shortest-path algorithm that includes driving, walking, biking, and all transit modes (e.g., bus, suburban bus, rail, commuter rail, and so on). For a given origin-destination pair and departure time, it generates the shortest path based on the traveler’s and the destination activity’s attributes, as well as the desired set of modes. The traveler may choose driving, walking to transit, biking to transit, park-and-ride (PNR), kiss-and-ride (KNR), or including bike-share services along their path, as well as utilizing transportation network company (TNC) services such as Uber or Lyft.

In a metropolitan region such as Chicago, there are 40 million trips on average on a given weekday. In order to

improve computational performance and the behavioral realism of the mode-choice model, some filtering heuristics were developed. As shown in Figure IV.1.2 there are several areas in the metropolitan region with no feasible walking access to any transit service. It is computationally infeasible to try finding walk-to-transit routes for these trips. As a result, a Dijkstra-based heuristic is developed. From every walking link in the multimodal network, the walking time and distance to the nearest transit stop/station are calculated and stored. It takes less than a minute to pre-calculate these distances and store them for each of the 123,000 walking links in the Chicago region. The mode-choice model of POLARIS retrieves that information and checks whether the walking distance from origin to transit (access) or the walking distance from transit to the destination (egress) is above the traveler- and activity-specific threshold (e.g., 1 km, 2 km). It is important to note that this feature is specific to the traveler (age, lifestyle, etc.), as well as to the activity (urgency, origin and destination locations, etc.).

Similarly, it is not realistic for a traveler to drive close to the destination for 40 minutes, get off, and then take transit to the destination and spend 5 minutes. Hence, similar heuristics are developed for drive-to-transit (e.g., PNR, KNR, and TNC access trips). From every road link in the multimodal network, the driving time and distance to the nearest transit stop/station are calculated and stored. Similarly, it takes less than half a minute to pre-calculate these distances and store them for each of the 56,000 driving links in the Chicago region. The mode-choice model of POLARIS retrieves that information and compares the driving distance from origin to transit (access, important for PNR, KNR, and TNC to transit) or the driving distance from transit to the destination (egress, important for TNC after transit) with the door-to-door (direct) driving distance. If the values are “too close” to each other, the drive-to/from-transit option is not feasible.

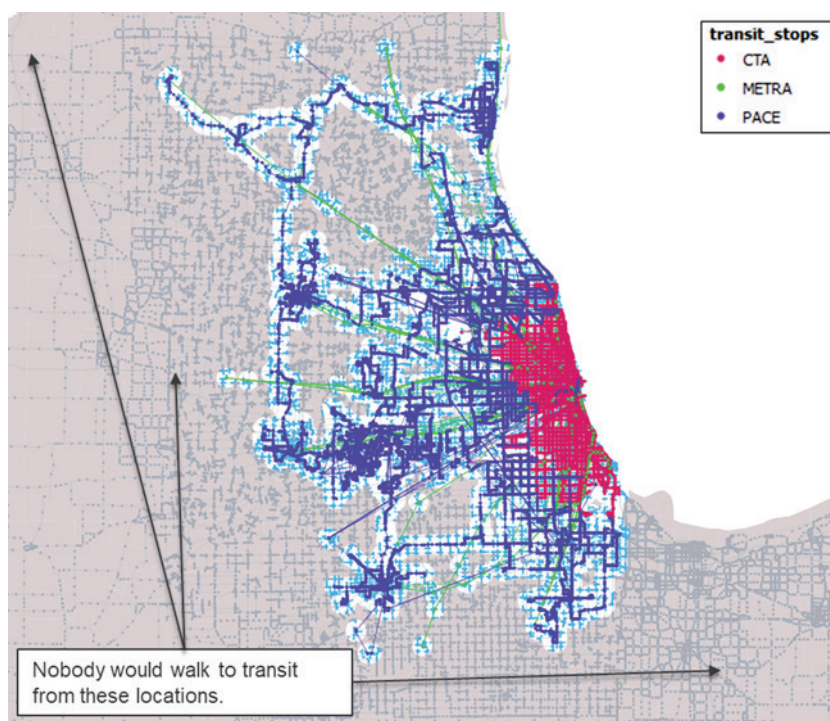


Figure IV.1.2 Filtering Heuristics for Locations with no Feasible Walking Access to/from Transit

Implementation of Complex Fare Structures

The POLARIS model was updated to read the General Transit Feed Specification (GTFS) (also used by Google Maps) fare structure provided by each transit agency. Depending on the agency, fares are collected based on number of boardings (reduced/free transfer fees), boarding and alighting stations, zones through

which the itinerary passes, and the transit lines used. For example, in the Chicago region, Chicago Transit Authority (CTA) and the Pace suburban bus service use a boarding-based fare system with reduced transfer fees. However, they enforce a two-hour limit from the first boarding for a subsequent boarding to count as a transfer. On the other hand, fares for Metra (the Chicago metropolitan area’s commuter rail system) are based on the boarding and alighting stations. These complex structures are successfully replicated in the TDIMA* algorithm. The algorithm tracks the monetary cost. Moreover, the monetary cost is also a factor in the route choice based on travelers’ activity-specific values of time. And finally, this monetary cost also informs the mode-choice model.

Multimodal Simulation

As discussed before, the mode choice model of POLARIS provides modes for every trip based on traveler and activity characteristics. The TDIMA* algorithm provides routes for each of these trips, some of which are intermodal. In order to obtain mobility and energy metrics, these trips must be simulated using a multimodal network representation. Figure IV.1.3 provides a detailed flowchart of multimodal simulation.

Initially, every traveler is moved in the network along his/her assigned route. If the current link is not a transit link, then the traveler drives, bikes, or walks to the end of the link according to the route assigned by the TDIMA* algorithm. If the traveler is already riding in a transit vehicle, and the current link is not a transit link, then the traveler alights the vehicle. If the link is a transit link, and the traveler is staying on board, then the traveler rides to the next node in the transit vehicle. If the traveler is standing, and a seat becomes available because of some other travelers alighting, then the traveler gets seated. If the link is a transit link, and the traveler is in a vehicle but has to transfer, then the traveler alights and waits for the next trip. If the link is a transit link, and the traveler is not in a vehicle, then the traveler waits for the next trip. At every arrival at the end of a link, two checks are performed: one is whether the traveler’s experience up to that point is close enough to the pre-trip experience determined by the router. By experience, we mean the “generalized cost of travel,” which is a weighted sum of cumulative walking time, biking time, driving time, in-transit-vehicle time, waiting time, monetary cost, and transfer penalties. If the experienced generalized cost is significantly higher than the pre-trip generalized cost, the rerouting event is triggered. In other words, the TDIMA* algorithm is called upon to find the best route from the link at which the traveler is located to the traveler’s destination. The rerouting event is also triggered if the traveler is rejected from boarding a transit vehicle because it is at capacity.

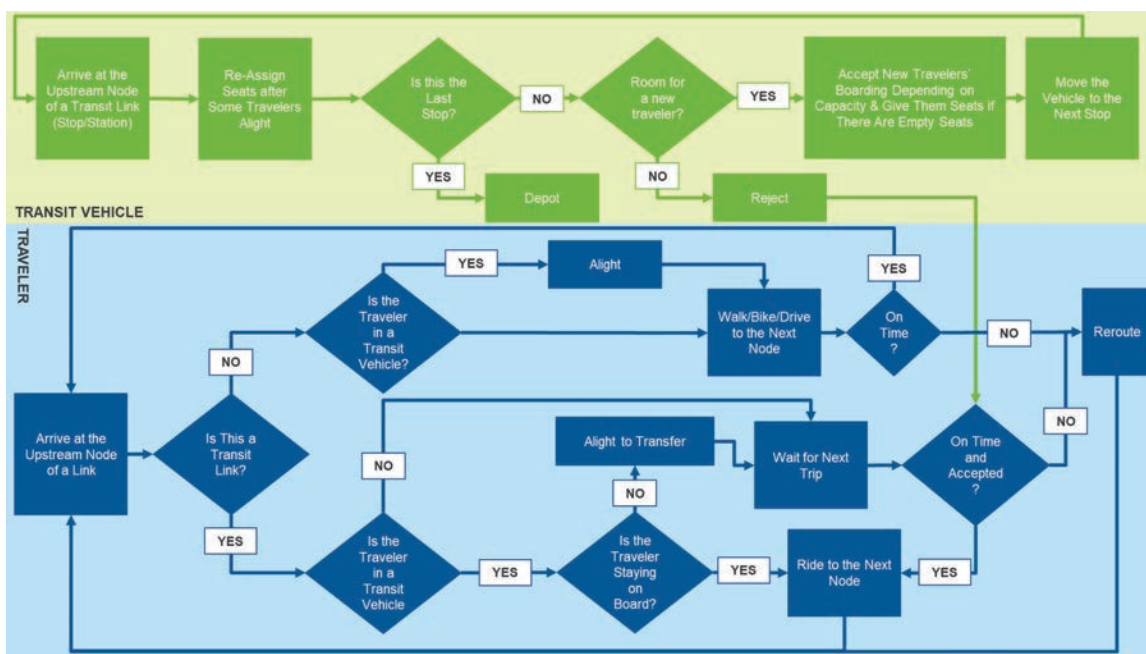


Figure IV.1.3 Flowchart for Multimodal Simulation

At the end of every traveler and transit vehicle trip, detailed trajectories are stored into the output database of POLARIS. For a traveler, this information includes pre-trip and actual arrival times; pre-trip and actual generalized cost; pre-trip and actual travel times of walking, biking, driving, in-transit-vehicle (seated or standing) separately; pre-trip and actual waiting counts; pre-trip and actual waiting times; and pre-trip and actual transfer penalties. These values are reported both on a link-by-link basis and at the trip level as a summary. Similarly, for a transit vehicle, pre-trip and actual arrival times; pre-trip and actual dwell times; pre-trip and actual travel times; travel distances; and seated and standing loads are reported both on a link-by-link basis and at the trip level as a summary.

Extend SVTriP for Transit Buses

The link-by-link transit vehicle trajectories also serve as an input to SVTriP. SVTriP receives average speeds, maximum speeds, and stopping times for a transit vehicle on a link-by-link basis and generates naturalistic 1-Hz speed profiles, as shown in Figure IV.1.4. The transition probability matrices (TPMs) used for the bus trips were generated using the data provided by the National Renewable Energy Laboratory (NREL) for 2,036 bus trips in the Twin Cities area. The trips add up to 81,000 vehicle-kilometers and 2,216 vehicle-hours.

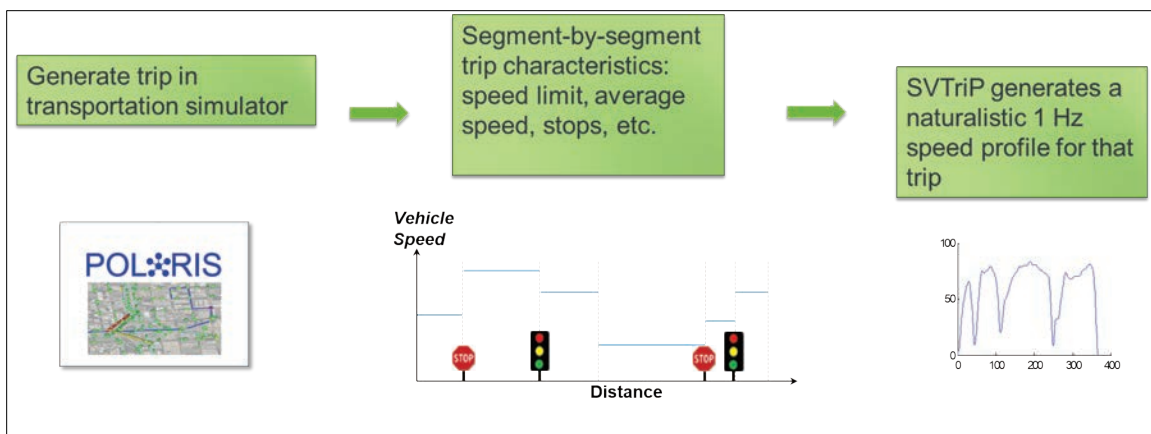


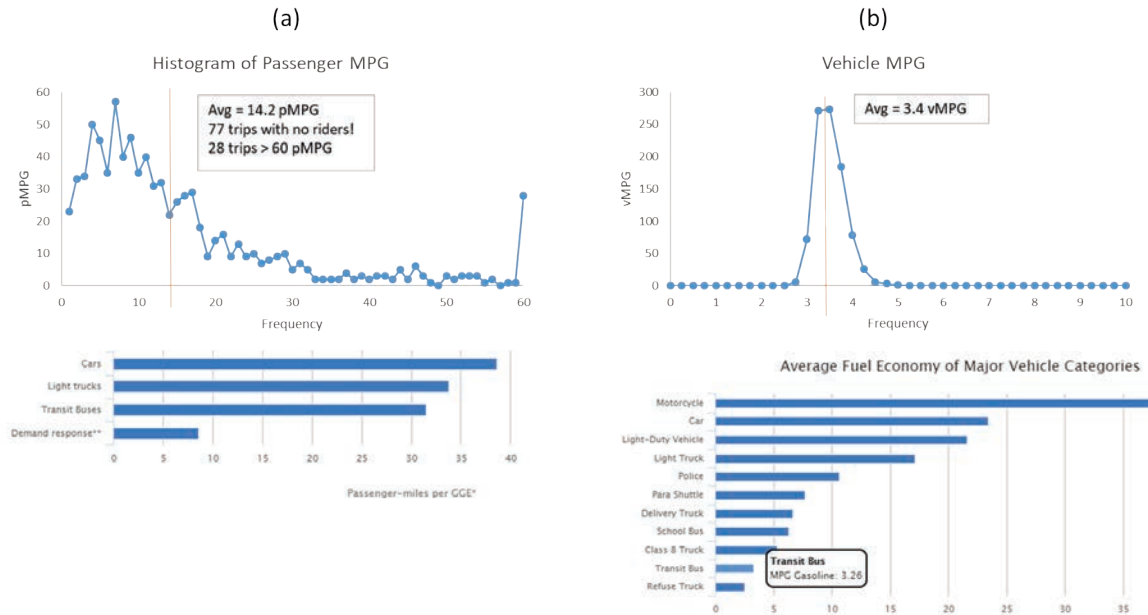
Figure IV.1.4 POLARIS to SVTriP

Results

The POLARIS-SVTriP-Autonomie full energy process has been implemented to the Bloomington, Illinois, network. Following are the network characteristics:

- 3,010 nodes
 - 2,540 street nodes
 - 470 transit stops/stations
- 15,062 links
 - 7,023 road
 - 8,068 walk
 - 511 transit
- 17 routes
- 31 patterns (route variations)
- 923 transit vehicle (bus) trips
- 37,035 multimodal traveler trips

Out of the 37,035 multimodal traveler trips, 5,006 of them involve buses. The remaining trips are for walking or bike trips only. Because the transit system is underutilized, the average passenger miles per gallon (pMPG) is 14.2, which is significantly below the nationwide average of 32 pMPG. On the other hand, the average vehicle miles per gallon (vMPG) is 3.4, which is very close to the national average of 3.26 vMPG. See Figure IV.1.5 for the distributions of pMPG and vMPG.



Source: Oak Ridge National Laboratory, Transportation Energy Data Book, 2016.

Figure IV.1.5 Histograms of (a) Passenger Miles per Gallon (left) and (b) Vehicle Miles per Gallon (right)

Conclusions

The POLARIS model has been significantly extended in order to simulate the movements of multimodal travelers and transit vehicles. The TDIMA* algorithm has been enhanced to include the fare structures of transit agencies. Smart heuristics have been developed to filter out infeasible walk-to-transit and drive-to-transit modes for the mode-choice evaluations. Moreover, SVTriP has been extended to include transit buses. The updated POLARIS -> SVTriP -> Autonomie process can successfully simulate the mobility and energy outcomes in a fully multimodal network representation.

Key Publications

1. Verbas, O., J. Auld, H. Ley, and R. Weimer. “A Time-Dependent Intermodal A* Algorithm for Heterogeneous Travelers with Efficient Heuristics.” Presented by O. Verbas at the 7th Innovations in Travel Demand Modeling (ITM) Conference, Lightning Talk Session 2A, Atlanta, Georgia, June 24–27, 2018.
2. Auld, J., O. Verbas, and M. Javanmardi. “Mode Choice Estimation and Simulation Using a New Intermodal Routing Algorithm and Transportation Big Data Sources.” Presented by O. Verbas at the 15th International Conference on Travel Behavior Research, Lectern Session 7G, Santa Barbara, California, July 15–20, 2018.

IV.2 Impact of Shared Mobility Use on Public Transit Services and Urban Form (LBNL, INL) [Task 1.4]

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Start Date: October 1, 2017	End Date: September 30, 2018	
Project Funding (FY18): \$75,000	DOE share: \$75,000	Non-DOE share: \$0

Project Introduction

Shared mobility systems, such as carsharing, 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 carsharing 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 carsharing 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 carsharing in that it provides one-way carsharing 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 carsharing 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 carsharing 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 carsharing?
5. Are certain patterns of home and work locations associated with modal shift in the presence of one-way carsharing?
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 carsharing? What other American cities might extract the greatest shifts toward multi-modalism from one-way carsharing 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 carsharing. 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

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.

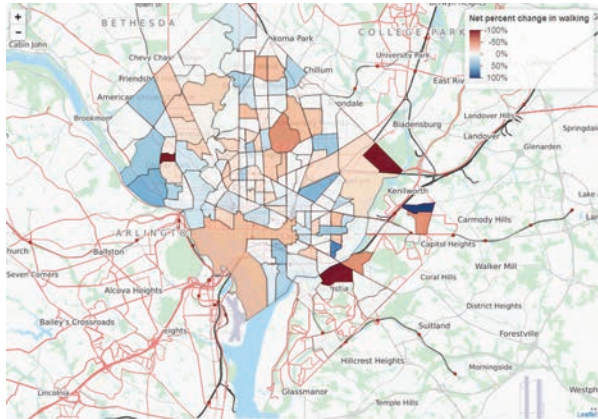
Researchers are using location data within the survey responses to illustrate the spatial distribution of respondent home and work locations. These impacts are being then be mapped to the urban environments of residence and work locations. The data is being overlaid with other urban attributes including 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 carsharing 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.

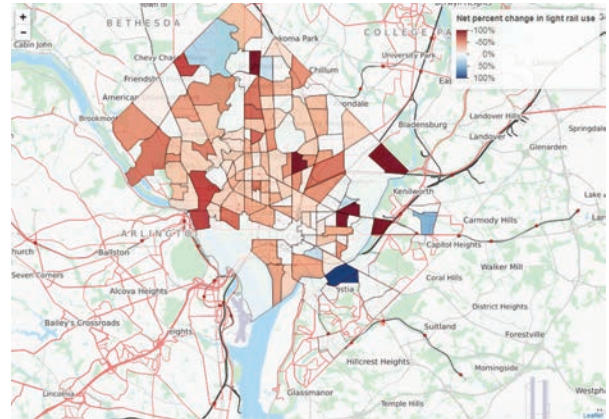
Results

Using data collected during the previous year, the research team has developed a series of maps that illustrate the distribution of impacts that car2go has had on travel behavior and on vehicle ownership. These results include a spatial analysis of mode shift in terms of walking, bus use, and rail use. In addition, the impacts of vehicle shedding and vehicle suppression are mapped across the five cities of study. The map of five impacts within Washington DC is shown in Figure IV.2.1. The spatial distribution shows some interesting dynamics at work. The net change in walking shows a mixed distribution of impacts across the city. Some areas in the city core had respondents reporting an increase in walking, whereas other regions in the core and outer edges of the city reported a decline. With respect to changes in bus and rail use, the patterns show a general shift away from both modes in the core of the city, and some increased use of both modes in the urban periphery. The impacts on vehicle ownership show distinct patterns as well. Vehicle shedding appears to be concentrated in the urban core, whereas suppression shows areas of concentration in the outer areas of the city.

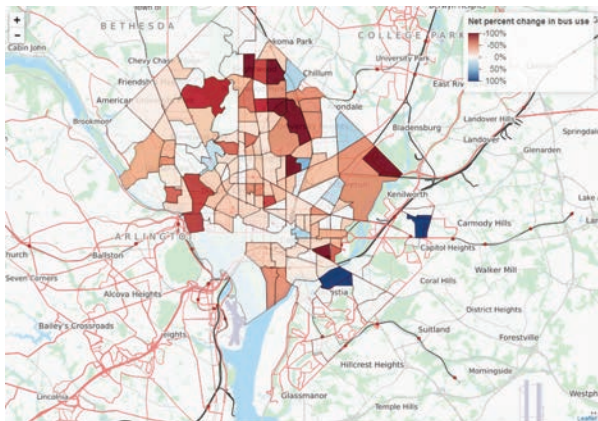
Net Change in Walking



Net Change in Rail use



Net Change in Bus Use



Vehicle Shedding



Vehicle Suppression

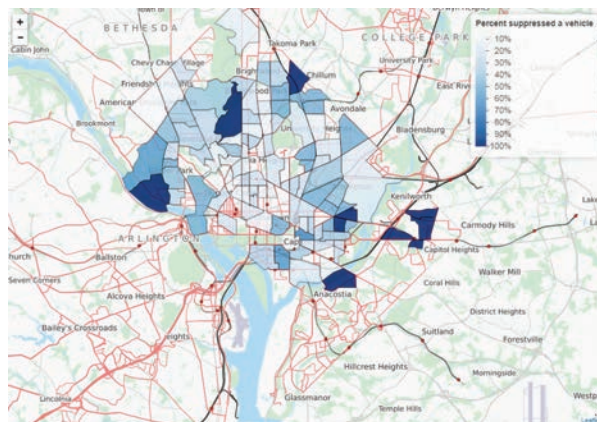


Figure IV.2.1 Map of Mode Shift and Vehicle Impacts in Washington DC due to car2go

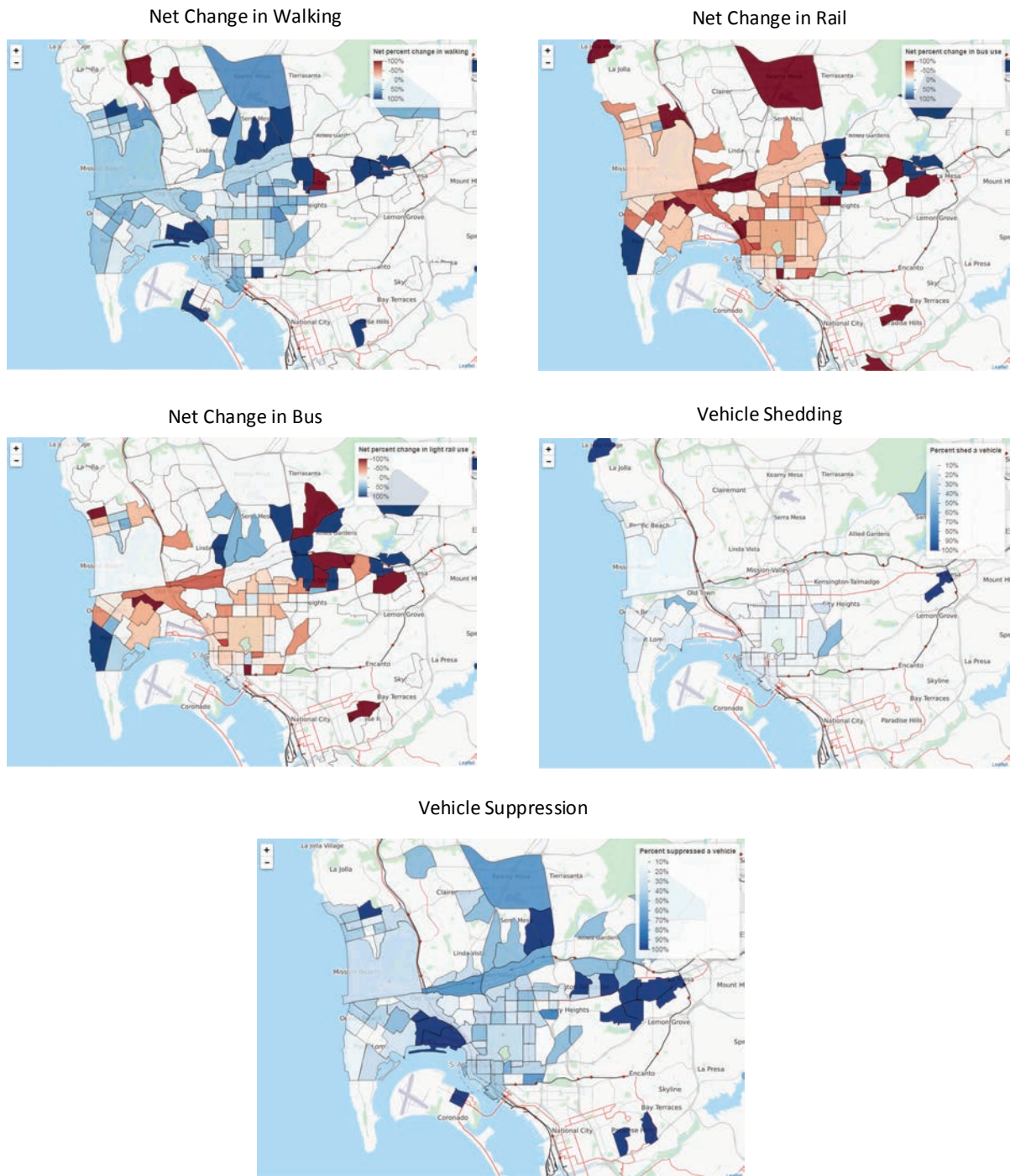


Figure IV.2.2 Map of Mode Shift and Vehicle Impacts in San Diego due to car2go

Different patterns of impact can emerge across different cities. For example, Figure IV.2.2 presents a map of the same impacts in San Diego and shows that car2go has a distribution of effects that are in some cases different from those observed in Washington DC. For example, there is a more widespread increase in walking. Similar to Washington DC, the change in rail and bus use are found mostly to be a reduction in the central areas of the city, while there are also selected regions of increase in public transit use around the periphery. Vehicle suppression impacts are somewhat similar between the two cities, while vehicle suppression exhibits no visible concentration in the core of San Diego, in contrast to the pattern shown in Washington DC.

The analysis of other cities, including Seattle, Calgary, and Vancouver, also reveal patterns that will be discussed in future project outputs. In addition, we have advanced the development of empirical models that explore the causal impacts of these changes based on a rich dataset of demographics and public transit infrastructure. These models will themselves present insights on the underlying factors that explain the noted changes in behavior. The models will also be applied in the coming year to illustrate how such data can be used to make projections of impacts from one-way carsharing with cities that may not yet have operational one-way carsharing systems.

Conclusions

Building on the progress from last year, the research team has completed a literature review of related research, advanced the spatial analysis of impacts from one-way carsharing, developed a database of demographic and transit attributes by census tract in the study cities, and developed preliminary models for impact estimation. In the coming year, the research team looks to complete the analysis and modeling, demonstrate the application of predictions on outside cities, and advance the results to academic publication.

Key Publications

1. Publications are pending. The project has advanced considerable work in analysis and modeling and expects to produce a journal article discussing the key outcomes of the study.

IV.3 Energy Analysis and Optimization of Multi-Modal Inter-City Freight Movement (NREL, ANL, INL) [Task 2.1]

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Start Date: October 1, 2017	End Date: September 30, 2018
Total Project Funding (FY18): \$350,000 (NREL),	DOE share: \$380,000 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, electrification, automation) 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 evaluate and understand the 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, electrification, and automation have demonstrated the potential to improve trucking freight efficiency. However, each of these is limited by a number of factors, including availability, applicability, and method of use. For instance, platooning as a technology is limited by 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 and document their overall potential for national scale energy impacts. In addition, the team will look at the ways that businesses can use different types of freight delivery methods to best achieve their goals while increasing efficiency and reducing energy costs. This may include shifts from one mode of delivery to another (such as using rail systems and trucks) and looking at different business methods such as off-hour transportation.

Approach

This project 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, develop baseline models, and identify new scenarios to analyze which can then be used as inputs to the agent-based models being developed under the SMART Mobility Consortium to examine specific impacts of technology and modal shift of freight movement. Scenarios address in FY17 included understanding ‘automation and platooning’ and understanding opportunities for ‘shift to truck’ scenarios resulting from changes in operating costs and efficiencies due to new technology. The scenarios to be address in FY18 included (and are summarized in this report include):

- What effect can electrified long haul trucks have on energy, time and cost for region or nationally and what % of inter-city freight movement (tonnage and ton-miles) that could be moved by a 300 mile- or 500 mile- electric trucks?
- What effect can ‘load pooling’ optimization have on energy, time and cost for city and national?
- Other scenarios identified for future analysis (FY19 and beyond) also include:
- What effect will optimized/increased connectivity and intelligence have to maximize truckload efficiency and what impact will this have on energy time and cost for region or nationally?
- What effect will dedicated lane use have and what impact will this have on energy, time and cost for region or nationally?
- What effect will ‘time of day scheduling’ have and what impact will this have on energy, time and cost for region or nationally?
- What is the lowest ‘cost’ (time + energy +infrastructure) option to accomplish same O-D as today?
- What effect will ultra-high efficiency trucks (beyond SuperTruck) have and what will the impact be on energy, time and cost for region and national?
- What effect will increased trailer capacity (double/triples) have on energy, time, cost, and congestion at regional and national level?
- What effect will fuel cell / H2 vehicles have and what impact will this have on energy, time and cost for region or nationally?
- What effect will increased or decreased driver cost have on modal share, energy for region or nationally?

Results

What effect will ‘electrified trucks’ have on national energy use? - Quantifying Opportunities of Electrified Freight Movement by Class 7-8 Trucks

We first summarized electric range and other major characteristics of future medium duty (Class 3-6) and heavy duty (Class7&8) electric trucks recently announced by several auto makers, shown in Table IV.3.1. The base price of Tesla Semi-300/500 are still higher than comparable diesel truck and other alternative heavy duty trucks, according to Argonne’s AFLEET model [1], shown in Figure IV.3.1.

Table IV.3.1 Performance Characteristics of Existing and Future Electric Trucks

Manufacturer	Name	Capacity (lbs)	Energy Consumption* (kWh/mi)	Battery Pack (kWh)	Range (mi)	Base Price \$	Available
Tesla	Tesla Semi - 500	80,000	2.00	1000	500	150,000	2019
Tesla	Tesla Semi - 300	80,000	2.00	600	300	180,000	2019
Tesla	Tesla Founders Semi	80,000	2.00			200,000	2019
Daimler	E-FUSO Vision ONE	24,250	1.40	300	215		2021
Daimler	FUSO eCanter	3.5 tons	1.04	83	80		Available now
Cummins	AEOS	44,000	1.40	140	100		2022

* Full payload, highway driving speed (55mph)

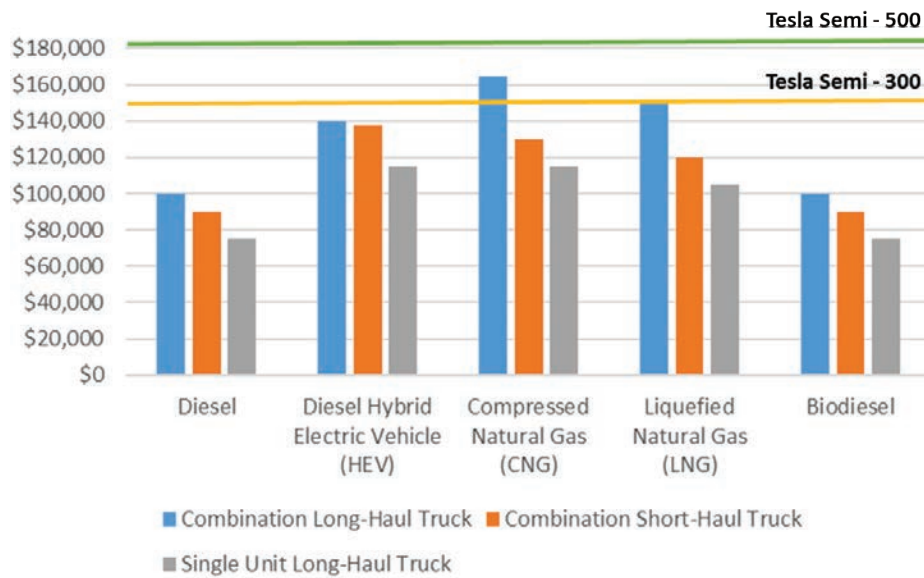


Figure IV.3.1 - Price Comparison of Heavy Duty Trucks with Different Powertrain Technologies

Second, we used FastSim [2] developed by the National Renewable Energy Laboratory to estimate energy consumption of a 500-mile electric truck. Truck energy efficiency varies with cargo mass and coefficient of aero drag. This analysis used a weighted highway driving cycle, numbers shown in Figure IV.3.2.

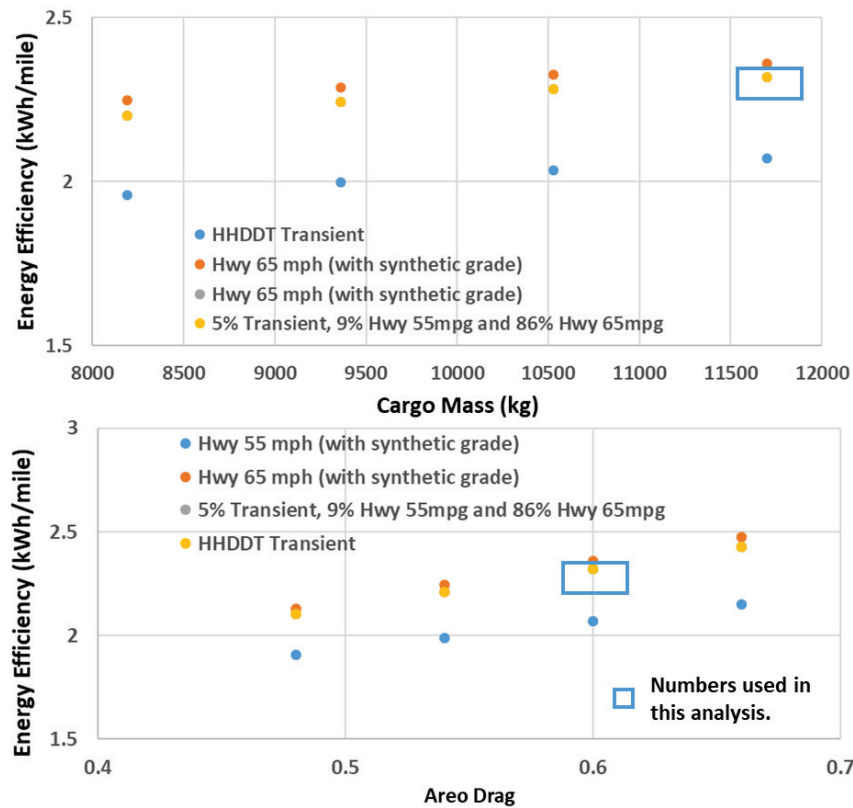


Figure IV.3.2 - Simulated Truck Energy Consumption (kwh/mile) a 500-mile electric truck

Based on projections of tonnages and ton-miles made by FHWA’s FAF 4.0 [3], we estimated % of truck ton-miles could be electrified using average length of haul between 123 freight zones (origin/destination) in the United States. Then, we estimated number of electrified heavy duty truck (Class 7&8) needed in 2045 on the road to fulfill the projected freight movement assuming using trucks with 300- or 500- miles electric range. From the number of electric trucks on the road, we estimated the electric truck market penetration from 2017 to 2045 using a logit function, formula (1). We estimated both low and high cases of the market shares (sales and stocks) assuming high and low truck load (tonnage per truck) and average annual truck mileage, about 60,000 miles. In average, if we assume each truck’s average load is at lower end, about 16 tons [4], then the number of electric trucks needed will increase, which leads to high sales and stock shares. If we assume each truck’s average load is at higher end, about 22 tons, then the number of electric trucks needed will decrease, which leads to low sales and stock shares As an example, Figure IV.3.3 shows estimated sales and stock shares of electric Class 7&8 truck needed in 2045 assuming all trucks have a 500-mile electric range.

$t = \delta + \ln [F\{t\} / (1 - F\{t\})] + \mu$ (1): δ and β are coefficients that become scalar factors determining the shape of the market penetration curve and μ is the error term.

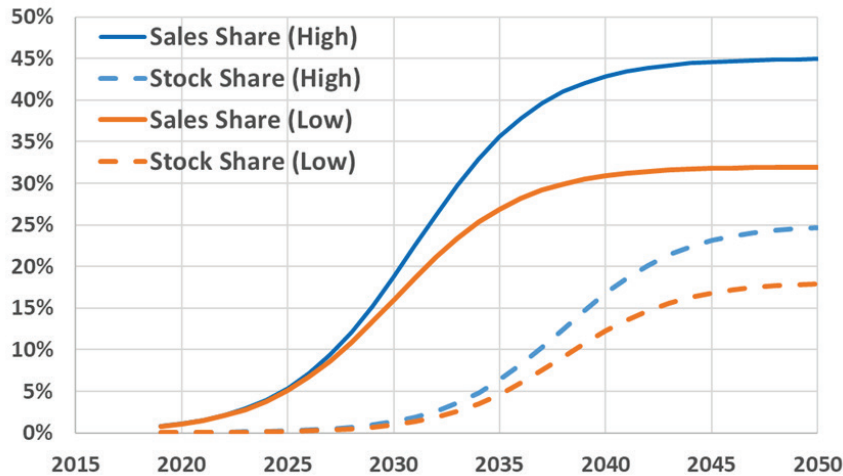


Figure IV.3.3 - Electric Class 7&8 Truck Market Shares (500-mi electric range)

Based on the sales share, we estimated the number of electric class 7&8 trucks on the road in 2045 using total number of class 7&8 trucks projected by EIA’s AEO 2017 [5] and heavy truck survival functions [6]. We assume the electric trucks will replace conventional diesel trucks. Using Argonne’s NEAT model [7], we could estimate the total energy consumption by different powertrain technologies in Class 7&8 truck sector.

Next, we estimated that electrified Class 7&8 electric truck with 500-mi electric range could potentially reduce the petroleum consumption by 1.61 quad in 2050, while the electricity consumption increases by 0.99 quad, comparing to EIA’s AEO2017 reference case, shown in Figure IV.3.4. Another scenario assuming 300-mi electric range shows that petroleum consumption by 1.14 quad in 2050, while the electricity consumption increases by 0.69 quad.

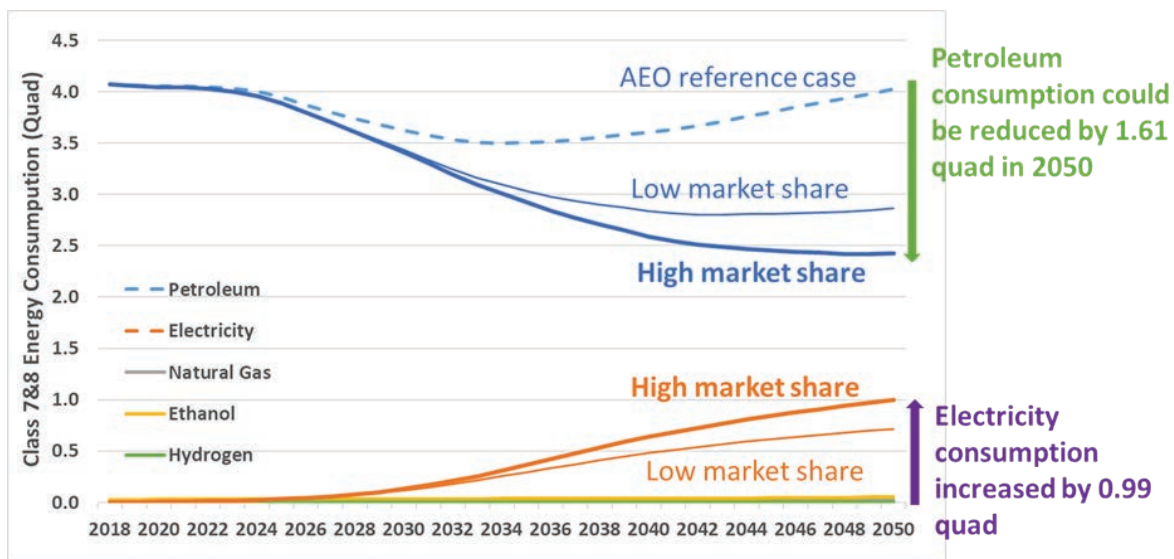


Figure IV.3.4 - Energy Impact of Electrified Class 7&8 Electric Truck in the United States (500-mi electric range)

Developing a Tour-Based Model for Inter-City Freight Movement - Analysis to Understand ‘Load Pooling’

In addition, a tour-based model with was developed to quantify the energy benefits of freight load pooling using multimodal shipping. Dijkstra’s shortest path algorithm was implemented to find the most energy efficient route for freight deliveries. The framework and the logic of the model are presented in Figure IV.3.5.

A multimodal freight network is developed by combining freeway, rail, and waterway. Then, taking energy intensity and freight OD pair as inputs, Dijkstra’s shortest path algorithm is ran on the network and output the optimized results for freight load pooling scenario. A baseline scenario was also developed for comparison and energy savings calculation. The baseline energy consumption is estimated using CFS data. The model framework was developed in R.

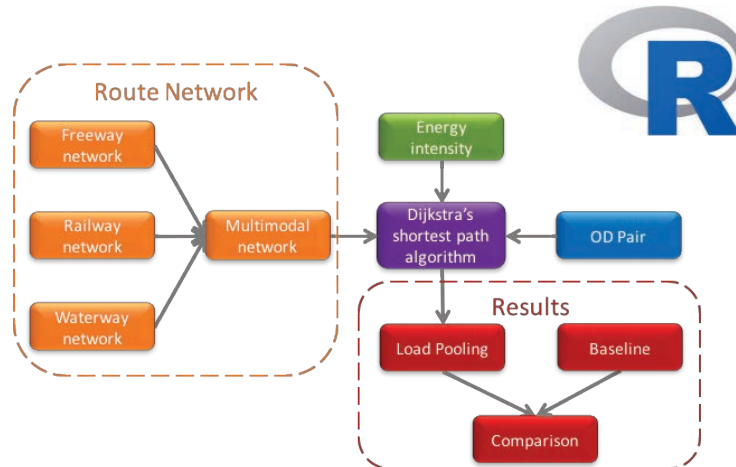


Figure IV.3.5 - Model framework and workflow.

In order to run Dijkstra’s shortest path algorithm and quantify the energy consumption, a multimodal freight network topology needs to be created. 69 major US metropolitan areas listed in CFS data were selected for the national level analysis. First, each individual network GIS shapefile (freeway, rail, and airport) was converted to a routable network and produce the topology of the network. A multimodal freight network topology was then created by joining topologies, as shown in Figure IV.3.6.

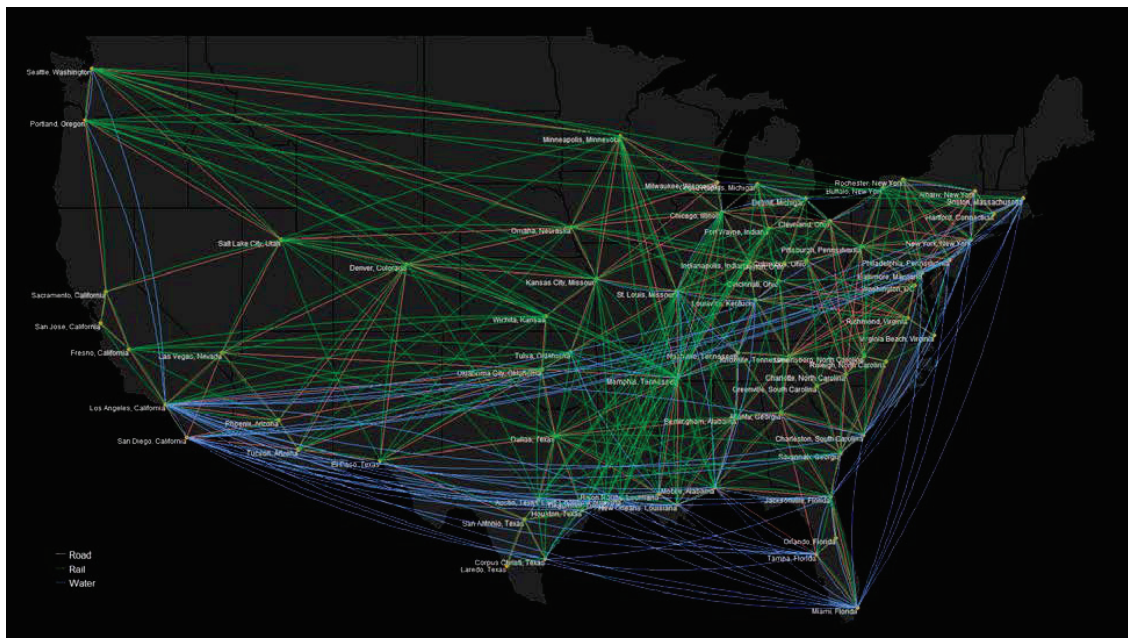


Figure IV.3.6 - Multimodal freight network topology and data

The national baseline modal share of freight shipment was obtained from 2012 CFS data, and it is shown in Table IV.3.2. At the national level, the majority of freight was shipped by truck and water. 45% of freight was transported by truck, and 35% of freight by water. Only around 10% of freight adopted multimodal shipment.

It is estimated that the national wide freight shipments consume 29,534,259 gallons of fuel. The freight volume assignment on the links of multimodal network topology is shown in Figure IV.3.7. The thickness of the link represents the volume. Purple, pink, green, and blue represents air, freeway, rail, and water.

Table IV.3.2 Baseline Modal Share of U.S.

MODE	TOTAL WEIGHT (Pound)	SHARE
Truck	5,226,979,561	45%
Rail	1,564,807,853	13%
Water	4,010,178,945	35%
Road - Rail	717,184,337	10%
Road - Water	53,733,426	0.5%
Air	21,420,152	0.2%

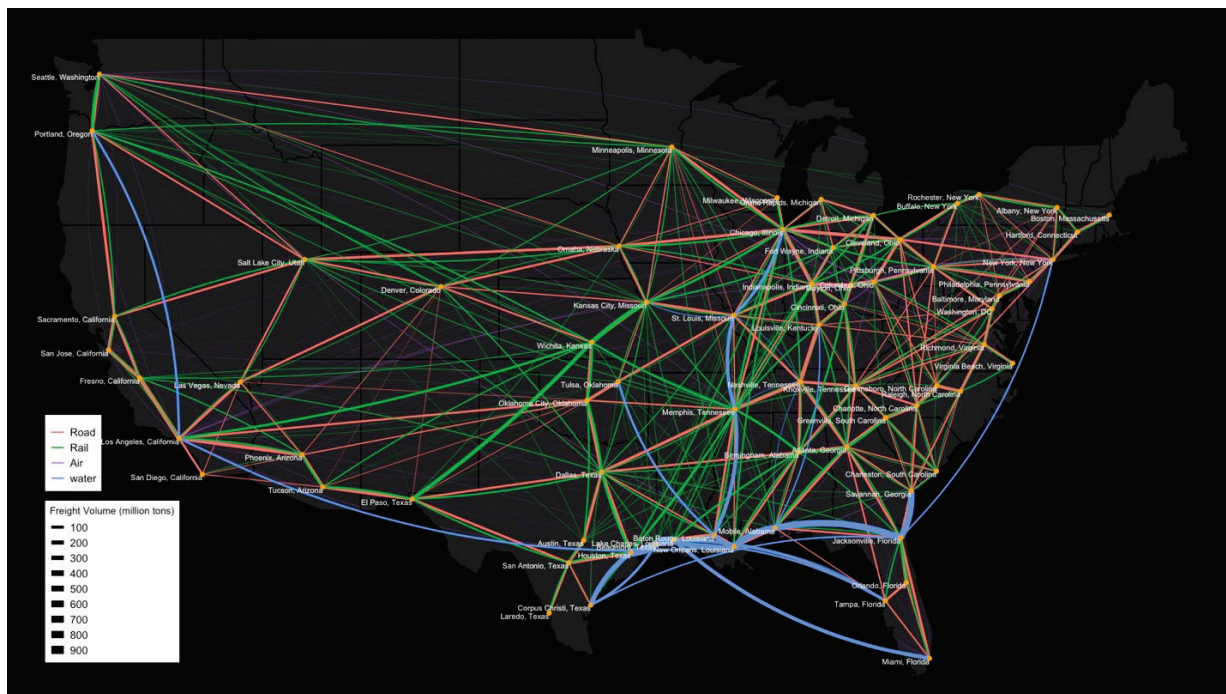


Figure IV.3.7 - Baseline Freight Volume Assignment of U.S.

After adopting load pooling, the national wide modal share of freight shipment is shown in Table IV.3.3. The freight volume assignment is shown in Figure IV.3.8. To minimize the energy consumption, the model also shifted all truck freight to rail, water, and water-rail. The estimated energy use is 12,043,536 gallons of fuel. The energy use comparison between baseline and load pooling are compared in Figure IV.3.9. Load pooling could potentially save 59% of total energy consumption for inter-city freight national wide.

Table IV.3.3 Loading Pooling Modal Share of U.S.

MODE	TOTAL WEIGHT (Pound)	SHARE
Truck	0	0%
Water	4,871,297,316	42%
Rail	3,626,224,113	31%
Water - Rail	3,075,362,693	27%
Air	30,798,672	0.2%

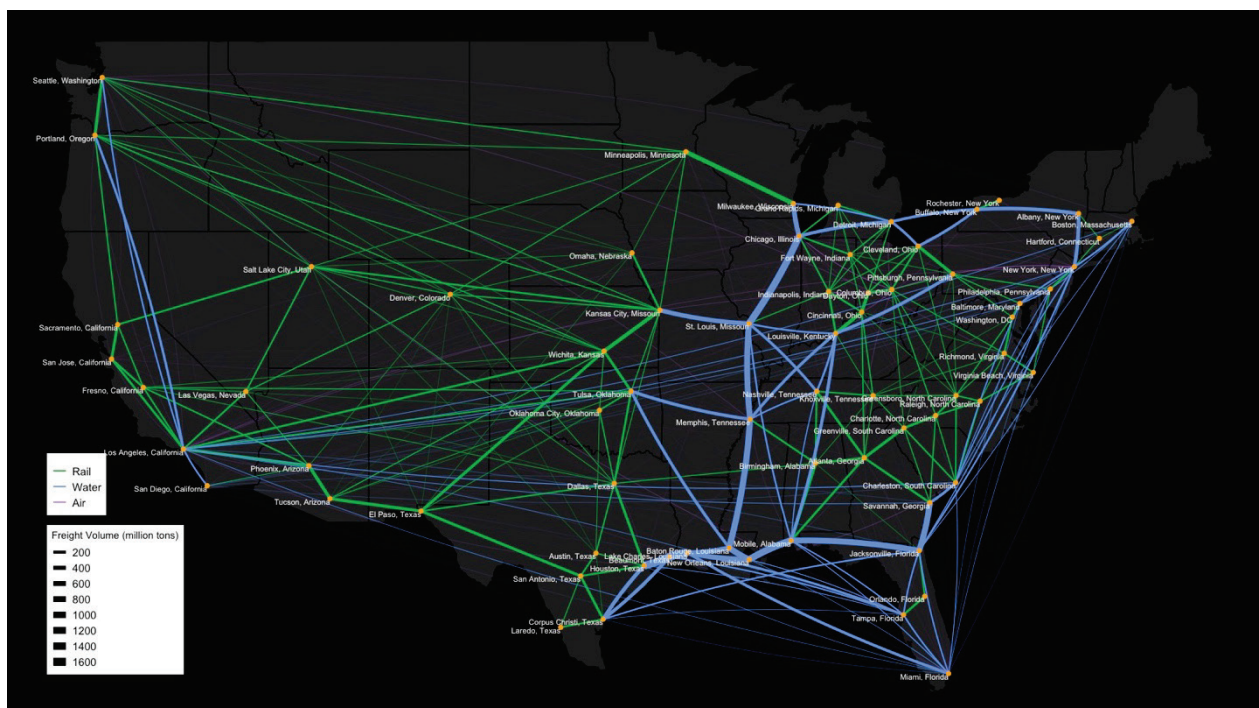


Figure IV.3.8 Load Pooling Freight Volume Assignment of U.S.

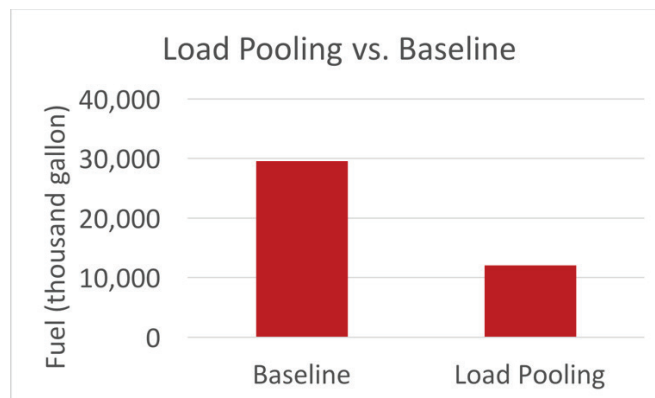


Figure IV.3.9 National wide comparison between load pooling and baseline.

Conclusions

National impact analysis found that electrified Class 7&8 electric truck with 500-mi electric range could potentially reduce the petroleum consumption by 1.61 quad in 2050, while the electricity consumption increases by 0.99 quad, comparing to EIA's AEO2017 reference case. In addition, a tour based model was developed and applied to at the nation scale. It demonstrated that modal shift was able to 59% of energy use national wide. To encourage modal shift from conventional truck to more fuel-efficient modes, more improvements need to be achieved to make rail and waterway more competitive and appealing to freight shipment, such as enhancing modal speed. Seamless modal transition is a necessity for load pooling since delay caused by modal transition could discourage multimodal shipment.

Beginning in FY18 with available funding/resources, NREL researchers have demonstrated a preliminary modeling method to identify opportunities for fuel/energy savings using CFS data combined with optimization techniques which can be used to evaluate scenarios such as load pooling and other considerations. The model was also applied to Columbus, OH region as well as the data available for the entire US (reported under separate report).

This method was able to provide initial results demonstrating that load pooling was ideally able to save 56% of energy use for freight shipment originated from Columbus, OH and 59% of energy use national wide. To encourage modal shift from conventional truck to more fuel-efficient modes and be able to approach these maximum levels.

More improvements need to be achieved to make rail and waterway more competitive and appealing (time and total cost) to freight shipment, such as enhancing modal speed.

Seamless modal transition is a necessity for load pooling since delay caused by modal transition could discourage multimodal shipment.

Key Publications

1. Y. Zhou and M. Rood, National Energy Impacts of Heavy Electric Truck Adoption for Freight. Submitted to Electric Vehicle Symposium 32, May, 2019, Lyon, France.

References

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Acknowledgements

This work is supported by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy (EERE), Vehicle Technologies Office (VTO). We thank David Anderson, program manager of Energy Efficient Mobility Systems, for his generous support. We also thank David Smith, the pillar lead of Multi-Modal for his support and guidance on this task.

IV.4 Optimization of Intra-City Freight Movement with New Delivery Methods (ORNL, INL, NREL) [Task 3.1]

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Project Introduction

This study considers multi-modal shifts, especially for the last-mile portion of freight delivery, using data obtained from the United Parcel Service (UPS) depot near Columbus, Ohio, and focuses on the potential for energy savings by incorporating these shifts in both vehicle type and routing configuration within the city of Columbus. A freight delivery demand estimation model was developed using socioeconomic, business, and land use data from the Mid-Ohio Regional Planning Commission (MORPC). A tour-based freight model was used to develop several scenarios to compare various modal and technology shifts to compare energy usage in kilowatt-hour estimates. Innovative means of freight delivery were considered for the alternative scenarios and included: electric class six trucks, electric delivery vans, parcel delivery lockers, drones, and the use of electric passenger vehicles for en-route deliveries. These alternatives were compared with the baseline scenario using a traditional petroleum-fueled, class six, delivery truck. Initial findings suggest that electric trucks paired with parcel delivery lockers reduce energy usage, especially in suburban neighborhoods. This study aims at providing decision makers, both in the private and public sector, with information to consider when determining suitable alternatives for energy efficient freight transport.

Objectives

This study is funded by the DOE through SMART Mobility and is a collaboration with the Oak Ridge National Laboratory (ORNL), Idaho National Laboratory (INL), the National Renewable Energy

Laboratory (NREL), UPS, and MORPC. Columbus is the Department of Transportation (DOT)'s Smart City Challenge winner and was chosen as the focus area for this study to develop methods for evaluating innovative means of delivering intra-city freight.

UPS and MORPC collaborated with ORNL, NREL, and INL and provided the necessary data for model development. The products of this study are intended to be used to evaluate multi-modal shifts in freight transport, especially for the last-mile portion of delivery. A freight delivery demand estimation model was developed to provide a means by which other cities can replicate this study in the absence of data from UPS or another parcel delivery company. The methodology for incorporating the use of tour-based models using innovative methods of freight transport and delivery was also developed.

Approach

The methodology developed, and the two, initial model types developed in this study: a freight delivery demand estimation model (in ArcGIS), and a tour-based freight delivery model (in TransCAD), are intended to be replicable in other locations. For the models, the Columbus UPS depot provided GPS data from a portion of their fleet. GPS data from 20, class six, delivery trucks were obtained by researchers at NREL during July 2017. Locational information, data on acceleration and vehicle performance were also included in the data logs. Extraneous data points were excluded, resulting in assumed delivery stops per vehicle. Once all of the assumed stops were obtained for each vehicle, the data points were manually processed to obtain average number of stops per vehicle per day, average starting and ending times, and so forth. Total delivery stop counts per Traffic Analysis Zone (TAZ) were tabulated, to be used in the estimation model. An estimation model was needed to create additional scenarios for areas of Columbus and Franklin County where data were lacking (Figure IV.4.1). Because this is a transportation study, data for the model were evaluated at the Traffic Analysis Zone (TAZ)-level, as TAZs are the typical unit of geographic analysis in transportation studies.

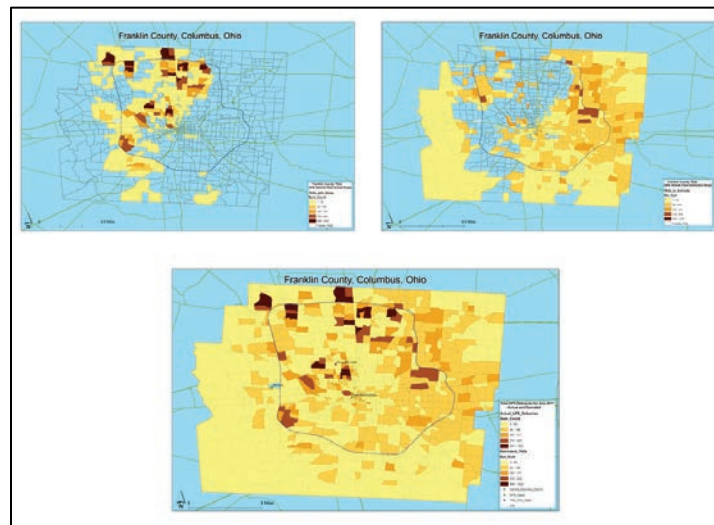


Figure IV.4.1 TAZs with actual GPS stop counts (upper left), TAZs with estimated counts from model (upper right), and all TAZs within Franklin County, Ohio with stop counts (center) (in ArcGIS)

TransCAD software was primarily used to model the baseline scenario and develop alternative multi-modal scenarios. The baseline scenario is the tour (depot to intermediate stops, returning back to depot) that a standard, class six, petroleum-fueled, delivery truck takes from the Columbus depot location, making all stops,

and returning back to the depot. It was determined that the shortest path routing function in TransCAD would be used for the modeling.

Several alternative scenarios were then developed to compare with the baseline case using the standard, class six (14 feet long, weighing four tons), petroleum-fueled, delivery truck. These initial alternative scenarios were developed to provide representative cases to compare energy usage by incorporating innovative freight delivery modes. For the initial alternative scenarios, the following modes were considered: fully-electric, class six, delivery trucks, fully-electric delivery vans, parcel delivery lockers at optimal locations relative to stops, electric drones, and fully-electric passenger vehicles using an en-route delivery system. Determination of energy estimates in kilowatt-hour were simply based on total mileage.

INL performed an initial round of testing using a Matrice 600 Pro hex-copter carrying different levels of weights and performing different types of delivery components (Figure IV.4.2). For each of the flight scenarios the logs of energy used by each motor was recorded, as well as the reported battery levels. When the testing was completed, the total energy needed to re-charge the battery was also recorded to provide an estimate of total true energy consumption. These scenarios allowed researchers to isolate and quantify which portions of the flight pattern were impacted by each component of a freight delivery: weight, hovering, flying, and speed. Figure IV.4.3 shows the total energy consumption that was needed for different parts of a one-minute hover test for different weights as recorded by the motors. For comparison, the energy record by testing of a Nissan Leaf is also included. The recorded components demonstrated that higher weights increased the total energy use in a relatively linear fashion until the weights approached the maximum weight for the drone. The greatest impact on total energy was observed to be the total time in flight so the faster speeds and lower flight heights (resulting in decreased time to rise to the proper elevation) decreased the total energy needed.

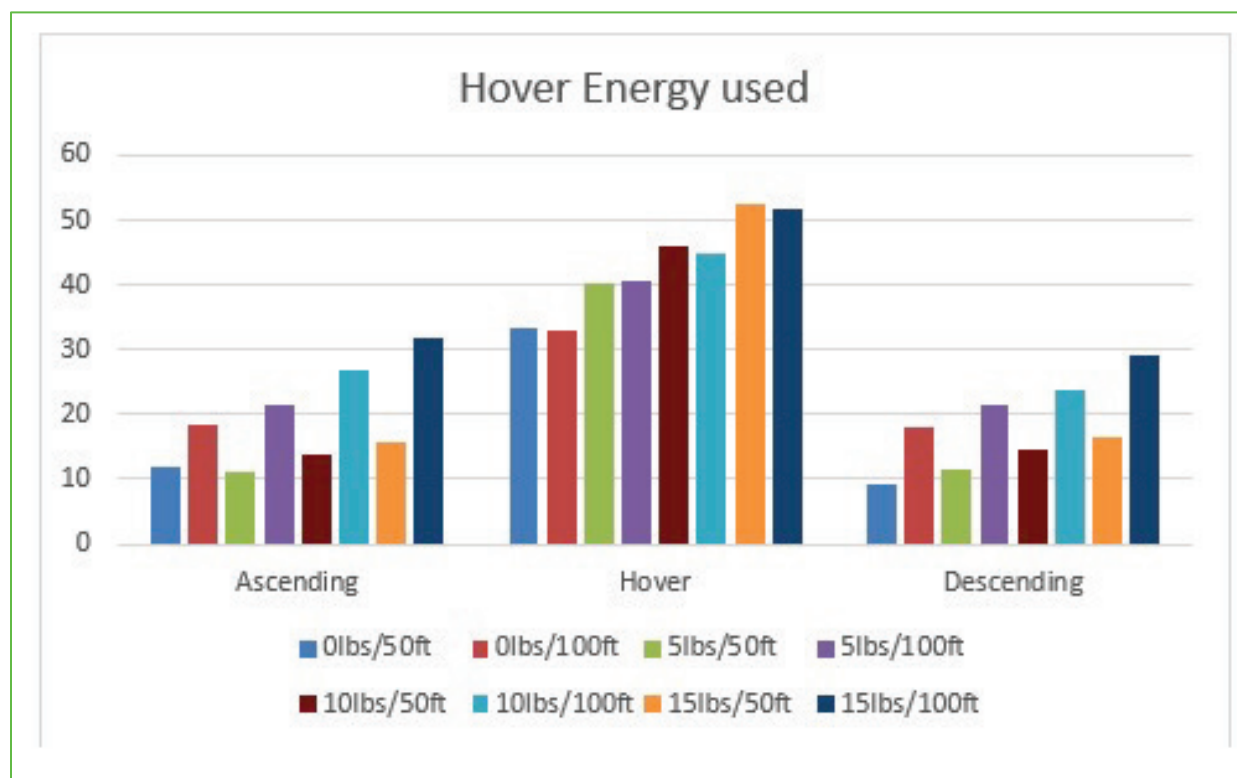


Figure IV.4.2 Energy consumption for different portions of a one-minute hover test reflect higher energy use as weights and flight times increase

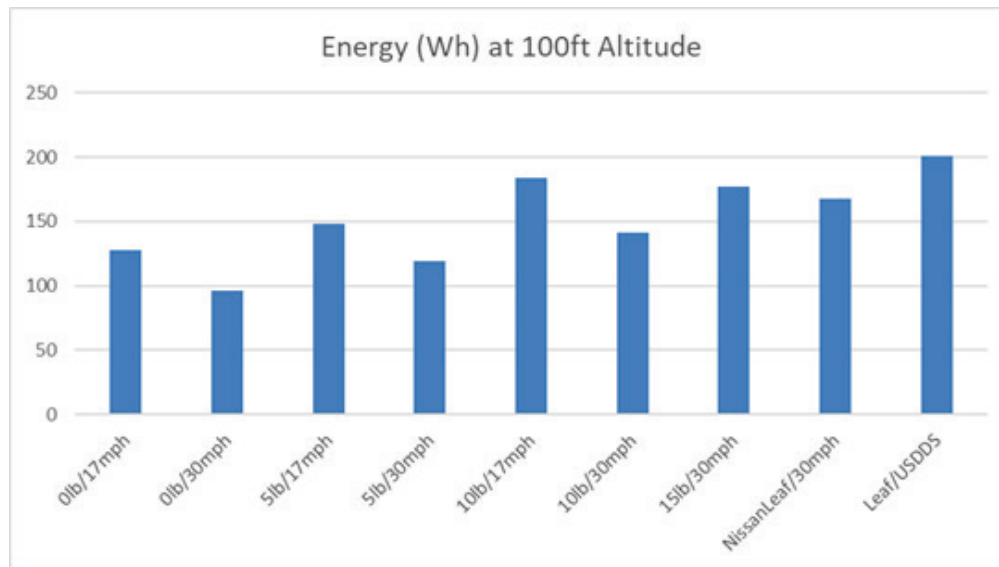


Figure IV.4.3 -Energy consumption at one-minute flight test with different speeds and weights.

Larger packages are comparable in energy use to an electric passenger car

Based on the observations, researchers were able to predict the total energy for each of the components of a flight pattern. The observations have demonstrated that the use of drones for delivery would have a significant energy use which may increase the overall total energy needed for delivery in comparison to conventional vehicles. The scenarios for how the drones will be used is significant in how the energy would be utilized and how it might benefit other aspects of the delivery business model.

Initially, the baseline and alternative scenarios were modeled in three tour configurations: 1) a tour from the depot to a single, urban TAZ with actual UPS GPS data points located near the city center; 2) a full tour from the depot, making all stops within multiple TAZs, and returning back to the depot; and lastly, 3) a tour from the depot to a single, suburban TAZ with estimated delivery stops based on the estimation model, and returning back to the depot. These three configurations were chosen to evaluate the energy saving potential for the different scenarios in different locations within the study area.

Results

The initial results from the model (Table IV.4.1 and Figure IV.4.4) with the tour configuration using the single, urban TAZ is not representative of the energy usage involved in completion of a full vehicle tour. However, it is exemplary of the potential reduction in energy usage made by incorporating the use of class six EV trucks in that the majority of the truck's mileage is within the stem portion of the route, or the distance from the depot to the TAZ. Because the TAZ chosen for the configuration is in a densely-developed, urban area, with through-streets and connectivity, the majority of mileage is in the stem, rather than in the distance traversed during deliveries. It is also evident that incorporating the use of lockers only results in a minimal reduction in energy usage. This is also due to the fact that the TAZ is densely-developed and there is connectivity within the street network. Thus, the overall distance traveled by the truck as it makes deliveries is not significantly reduced by incorporating a locker.

Table IV.4.1 Energy estimates for baseline and alternative scenarios

Scenario	Mode	Energy Usage (kWh/mile)	Total Energy Usage (single, urban TAZ)	Total Energy Usage (full, urban tour)	Total Energy Usage (single, suburban TAZ)
Baseline – Class 6 truck makes deliveries from depot	Class 6 truck	4.29	69.11	128.96	114.46
Alternative – EV class 6 truck makes deliveries from depot	Class 6 EV truck	1	16.11	30.06	26.68
Alternative – Class 6 truck makes deliveries to UPS; EV van makes deliveries	EV Van (eNV200)	.56	71.13	78.21	89.24
Alternative – Class 6 truck makes deliveries to lockers	Class 6 truck	4.29	66.67	66.67	98.46
Alternative – EV class 6 truck makes deliveries to lockers	Class 6 EV truck	1	15.54	15.54	22.95
Alternative – Class 6 truck makes deliveries by drones	Drone	.1	67.15	112.03	99.08
Alternative – Class 6 truck makes deliveries to UPS; passenger vehicle makes deliveries en-route	Passenger vehicle (Nissan Leaf)	.34	69.13	71.28	86.61

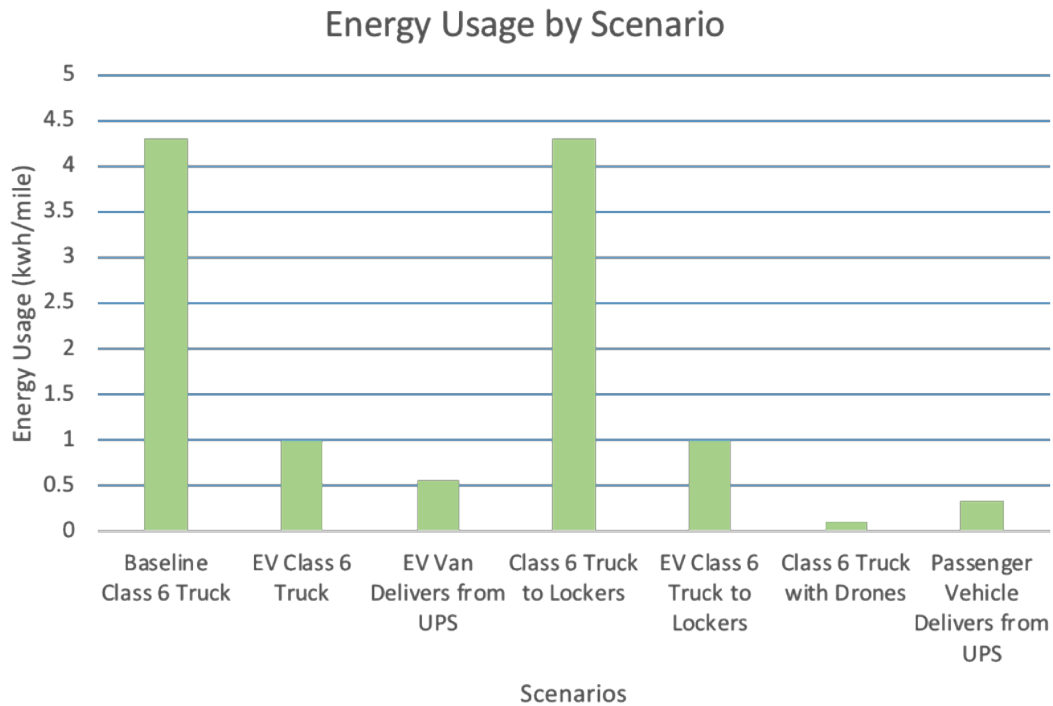


Figure IV.4.4 Energy consumption rate (kwh/mile) for baseline and alternative scenarios

The results from the model (Figure IV.4.5) using the full tour (from depot to all stops within the tour), are such that scenario three, using the class six EV truck, making deliveries to an optimal or centralized locker location, results in significantly lower energy usage than the remaining scenarios. Both scenarios involving the use of the class six EV truck resulted in substantially lower energy usage. This is not surprising, considering that the kwh/mile estimates are approximately one, compared with approximately 4.3 kwh/mile for the baseline.



Figure IV.4.5 Energy consumption at one-minute flight test with different speeds and weights. Larger packages are comparable in energy use to an electric passenger car

The two scenarios incorporating the use of the EV delivery van and the passenger EV are similar in energy usage estimates, as both vehicle types have similar kwh/mile estimates. However, scenario two, involving the EV delivery van, would have significantly lower estimates if a class six EV truck were considered for the scenario.

Lastly, it is not surprising that the energy usage estimates for scenario five, using drones to make final deliveries, is the second highest estimate of all of the scenarios. This is not surprising because the scenario requires the drone to make single deliveries (origin to destination), rather than making multiple deliveries before returning to the delivery truck, either at the origin location or en-route to the final delivery location. A more efficient use of drones would likely result in lower energy estimates.

The results from the model using the configuration with the single, suburban TAZ, as with the single, urban TAZ, is not necessarily representative of the energy usage involved in completion of a full tour. However, it is representative of the potential reduction in energy usage by incorporating the use of class six EV trucks, as the stem portion (distance from depot to TAZ) makes up the majority of the distance traveled by the truck. Also, it is representative of the potential reduction in energy usage by incorporating the use of parcel lockers. This is due to the fact that, in suburban areas, which typically contain subdivisions with cul-de-sacs and fewer through-streets, the placement of lockers at the entrance to a subdivision prevents the need for the truck to travel within the subdivision and avoids the need for the truck to turn around in the cul-de-sacs, which ultimately reduces the overall distance of the tour. By combining the usage of class six EV trucks with lockers, there appears to be the potential to further reduce energy usage in suburban locations.

Conclusions

Overall, it appears that fully-electric delivery trucks will significantly reduce energy usage, especially in the stem (long-haul) portion of tours where the truck travels a relatively greater distance to arrive at the cluster of TAZs to make deliveries. Parcel lockers also appear to reduce energy usage in suburban locations where there are fewer through-streets and more cul-de-sacs because mileage is significantly reduced. Lastly, pairing fully-electric delivery trucks with parcel delivery lockers will also further reduce energy usage, although modes to lockers needs to be considered to evaluate overall energy usage.

Additional GPS data is needed to further improve upon the models and resulting scenarios. Because this study was limited to using only a relatively small sample set, it is necessary to incorporate additional GPS data from UPS, or other parcel delivery companies, to better evaluate seasonal fluctuations in delivery demand, as well as other factors that influence delivery demand in TAZs.

Refinement of the drone scenarios will likely result in more accurate energy estimates that will better reflect the potential for efficient parcel delivery. Additional scenarios have been developed, including the launching of the drones from vehicles during the delivery routine, and optimizing a delivery route to avoid additional miles using drones. The current testing has recorded temperature, wind speed, altitude, and flight patterns. Additional testing may provide more specific impacts of these components as they change.

Although the results from this study are rather approximate, they provide insight into multi-modal freight delivery scenarios that can be incorporated into real-world routing examples to save energy usage. This study is significant in that it contributes to the current body of knowledge on tour-based freight modeling, GIS techniques in transportation systems engineering, and preliminary research and model development in energy efficient, multi-modal freight transport.

Key Publications

1. Moore, Amy M. *Optimization of Intra-City Freight Movement with New Delivery Methods*. Transportation Research Board Annual Meeting Compendium of Papers. (January 2019).
2. Hou, Y., Moore, A., Duran, A., Walkowicz, K., and Smith, D. *A Hybrid Tour-Based Model for Energy Analysis of Multi-Modal Intra-City Freight: A Case Study of Autonomous Electric Vehicles*. Transportation Research Board Annual Meeting Compendium of Papers. (January 2019).

V SMART Mobility - Urban Science (US)

V.1 SMART Mobility Data and Models Informing Smart Cities (NREL, INL) [Task 2.1.1]

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Project Introduction

This task supports the Urban Science pillar of the Department of Energy’s SMART Mobility effort through research focused on assessing the landscape of data and models in emerging smart cities. Foundational efforts to date, have included 1) providing a data and modeling resources report to help further integrate between transportation research and practice and with the growing reality that advanced transportation, mobility services, and infrastructure modernization are of increasing interest to cities, 2) examine data and modeling solutions within multiple cities, and 3) down-select on city case studies to work together on testing and scaling of urban science using available data and new primary data collected with inputs/validation from local city and regional partners. A focus is on factors that influence mobility options (e.g., travel time, costs, access to opportunities, and emerging mobility energy productivity metric/s) and associated energy-related impacts (e.g., fuel spent, vehicle miles traveled, costs to households) specific to new urban automated, connected, electric and shared mobility strategies developed and evaluated with partner cities. These cities comprise case examples where knowledge generated and coupled mobility-energy assessments can advance efforts across all 498 U.S. urban areas.

These efforts have placed emphasis in exploring advances in urban transportation data and modeling to develop, for analysis purposes, a robust, sophisticated and practical framework supporting the ultimate goal of providing an efficient, safe and sustainable mobility system for passenger and goods movement.

Objectives

This project aims to:

- Provide objective and quantifiable data that fills key knowledge gaps, which can be used in modeling/analysis efforts that address questions on how SMART technologies (ACES) impacts urban infrastructure, travelers, and energy.

- A focus on the effects of Mobility as a Service (MaaS) at airports, which are unique trip generation sites
- Address key research question/s, including:
 - How will ACES impact diverse urban travelers, systems, & services?
 - Long-term energy/travel impacts from changing urban environments?

Mobility options such as shared-use, electric vehicles, micro-transit, connected and automated vehicles and dynamic (real-time) information are already or expected to be part of the daily activities in the near-future, but their effect on the overall transportation system is not yet evident. For example, the use of electric vehicles is expected to reduce energy intensity, but the increase of connected vehicles may or not reduce congestion unless there is a dedicated lane. Similarly, automated vehicles could provide first and last mile accessibility to transit services negating the need for park-n-ride facilities or completely change mode choices with user preferences shifting to Shared Automated Vehicles (SAV) from traditional fixed-route transit services. In addition to the technological advances on the supply side, the opportunity facing us today is making demand management more robust by leveraging technology, behavioral insights, new urban system integration goals, and institutional readiness to overcome barriers inhibiting discovering and selecting a new and efficient mode not used before. As such, cities around the US are fully engaged in developing surveys, reports and plans that may provide a blueprint to prioritize investments via exploring behavioral impacts and system performance.

Approach

The approach for this project includes:

- TNC /MaaS data collection & analysis at major mobility hubs, such as airports and other key destinations, to characterize mobility/energy impacts using novel collection methods that will circumvent relying directly on TNC companies for data informing critical analysis insights.
- Obtaining direct access to city, regional, state databases to characterize mobility/ energy/behavioral impacts from EVs, AVs, other advanced tech & MaaS adoption – overcoming data gaps and obtaining highest possible detail & resolution for analyses to help inform a typology to national impact analysis
- Collaborating with industry (Strategic Vision), city networks (NLC, ACEEE) & others on Smart City survey/s, indicators/metrics to assess/ benchmark/predict MaaS in cities potential, adoption rates, design typologies and address Smart City questions at district/urban scales.

An alignment across urban science tasks enables the research team to bring new data and modeling methods related to Mobility as a Service (TNCs, Car-Sharing, Ride-Sharing and others), automated vehicles and other emerging mobility choices that will extend existing travel demand models and be transferrable to additional cities and regions. This has also included considerations for development of the Mobility-Energy-Productivity (MEP) metric and implementation approaches for airport- behavioral models, to employer provided mobility optimization, & district-scale on-demand services modeling.

Results

Quarter 1

- Initiated collection of airport data specific parking and TNC impacts. Full data sets were obtained for Denver, Portland and San Francisco. Partial data sets were gathered for another five cities.
- Initial analysis yields consistent patterns in TNC adoption, along with parking and rental car decline. Information is being prepared for publication and presentation (Feb Pillar meeting call)
- Data Use Agreement with Ohio BMV is being negotiated, issues with indemnification remain unresolved.

- Collaborated with Strategic vision in shaping its 2017 ride-hailing survey, investigating how to make it a market-research tool for Smart Cities, as well as contribute to SMART research.

Quarter 2

- Data sets obtained for eight airports and collaborations with city-university research partners to initialize new behavioral models that encompass and help to predict shifts in TNC, parking, transit and car rental demand.
- Initial analysis yields consistent patterns in TNC adoption, along with parking and rental car decline. Paper accepted for publication and presentation (ITS-America 2018, Detroit, MI)
- New registration data emerging with Ohio, New York, and next is Colorado and California.
- Collaborated with Strategic vision in shaping its 2018 ride-hailing survey with cities, investigating how to make it a market-research tool with city webinar, and so to contribute to our research.

As shown in Figure V.1.1, an airport is one of the most important assets for a region's economic development and connectivity with the rest of the nation and world. Key aspects for investigation of energy efficient mobility at airports is ground transportation including factors ranging from the infrastructure, mobility services, and associated revenues. Data is critical to understand the maturity of new mobility services that can inform both cities and airports on how to respond, approach, manage, and adapt to the challenges, opportunities, and uncertainties associated with shifts in new mobility that influence human behavior, energy-efficiency and sustainability strategies. With airport parking revenue in decline, and ride-hailing services rising, the shifts in revenues for ground transportation airports offers an option to explore the pace of transitions and adaptations in the new emerging mobility landscape, and present an opportunity to analyze how future adaptations could support more energy-efficient scenarios.

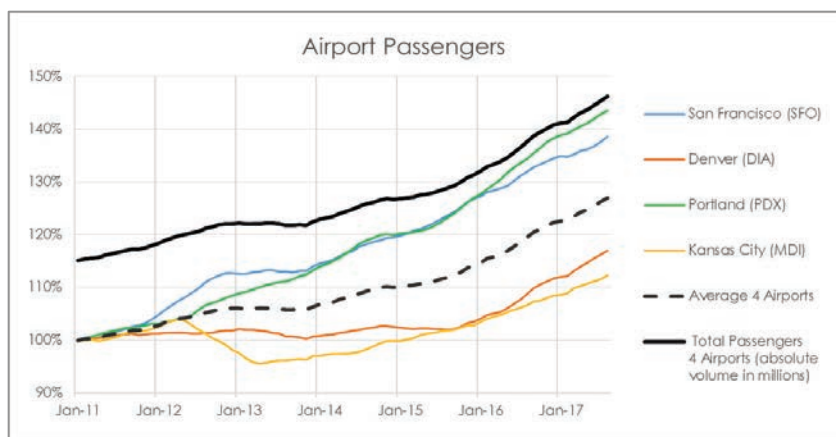


Figure V.1.1. Airport Passengers at Four Cities of Focus (Source: NREL working paper)

Quarter 3

- Published initial analyses of airport data specific to parking and car rental revenue shifts associated with TNC impacts, transit services, and airport modernization.
- Next analyses focused on energy and new mobility megatrends for airports and cities
- Investigating the feasibility of initializing a behavior model, with collaborators, combining the information from the data collection at airports with O-D patterns, and associated socio-economic data, related to travel demand to airports

- New vehicle registration data collected for Ohio, New York. Next is Colorado and California. Analysis of data (in partnership with Smart Columbus) revealed that single snapshot of Ohio BMV data was insufficient to obtain percentage of new EVs sold, a key performance metric in Ohio. A history of quarterly snapshots of the Ohio BMV registrations is being collection to use differences in registrations to assess EV adoption, while relying on industry provided data for Smart Columbus Metrics.
- Next analyses possible with new parking data across five U.S. campuses; and new TNC driver-side survey data across 11 US cities – to inform mobility energy productivity and new components to urban mobility and energy modeling.
- Exploration of new approaches for occupancy measurement is in development for cities and airports

Quarter 4

- Published initial analyses and submitted second paper on airport data specific to parking and car rental revenue shifts associated with TNC impacts, transit services, and airport modernization. Data sets being updated across eight airports to enable energy efficient airport-city connectivity and modeling; follow-on collaborations underway with airports, city to university research partners to initialize behavioral models that encompass and help analyze shifts in TNC, parking, transit, EV demands.
- Information gained from airport studies is seeding collaborative with HPC for airport work for DFW airport.
- Investigating the feasibility of initializing a behavior model in collaboration with US 2.2.1 and other SMART projects, combining information from occupancy/vehicle registration data collection to airport and employer-provided mobility data collection focused on O-D patterns, socio-economic data, pooling and travel demand shifts.
- Mobility data collection on TNCs, Rental Car Incentive Pilots and Vehicle Registrations
- Collecting/mapping data for NYC and NY State (with widely available open data) focused on TNCs to new mobility surveys focused on mode replacement
- Continued collaboration with Strategic Vision in shaping their anticipated Ride-Hail experience survey, and convening Smart City stakeholders for further input.

NREL has been in collaboration with Barbara Cohn, newly appointed Chief Data Officer for the Colorado Department of Transportation, and formerly with the New York State. Ms. Cohn was instrumental in NY's open data initiatives which led to NY being one of the first (and still very few states) that provides access to vehicle registration through a web portal. Her insight is guiding NREL to develop avenues for direct access to registration data in Colorado – as well as other states. In Ohio, the Smart Columbus initiative and associated reporting activities has resulted in the Ohio DOT pledging to work directly with the Ohio BMV to produce quarterly summaries reflecting the adoption of advanced fuel vehicles within the state, and reported at appropriate geographic resolution (such as zip code or even census block) so that it can be used for analysis and planning.

NREL is also collaborating with Atlas Policy, Nick Nigro, who is leading an initiative to acquire such data from multiple states. Atlas has achieved results with a handful of states, and is actively soliciting additional state partners. Strategic Vision, assisted by NREL, conducted a webinar on the potential to implement city-level surveys of TNC drivers/use among cities identified as having interest in smart transportation. An outcome of this webinar was continued motivation/rationale for TNC/MaaS/RUTS annual survey in cities, featuring survey design that builds on more recent literature/ key gaps and breakdowns by different urban traveler demographics. An example of the interest in emerging alternative fuel vehicles by generation is shown in , derived Figure V.1.2 from Strategic Vision survey data.

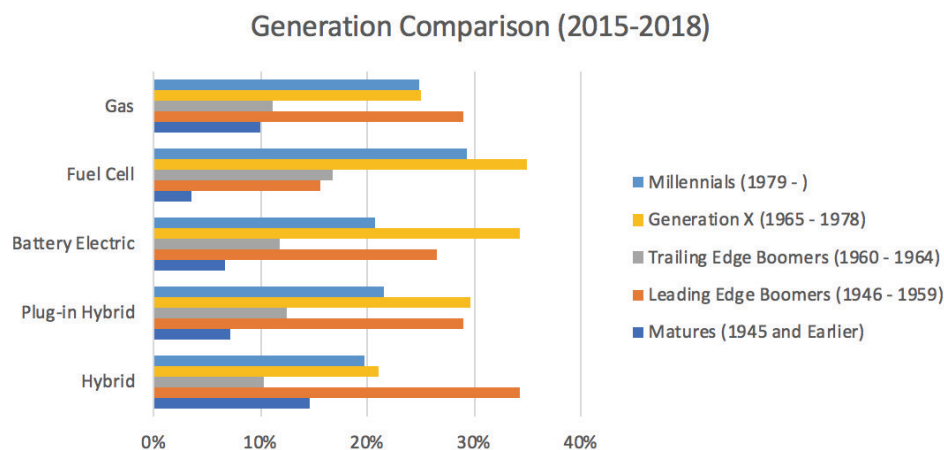


Figure V.1.2 Comparison of Interest in Alternative Fuel Vehicles by Generation (Source: Strategic Vision, 2018)

As research in this area begins to grow, the team aims to keep apprised of developments. Recent advancements that inform our efforts include:

- Bruce Schaller’s New York study – (<http://www.schallerconsult.com/rideservices/index.html>) arguing that TNCs are congesting urban areas, replacing transit and generally increasing traffic volumes.
- Regina Clewlow (formerly of UC Davis) continues to perform leading survey work. Her recent paper from last year (https://itspubs.ucdavis.edu/wp-content/themes/ucdavis/pubs/download_pdf.php?id=2752) - documents the numbers of people using TNCs, the modes they are diverting from, etc.
- Knowledge gap identified: No publication to date gets to *WHY* people are choosing TNCs over transit, walk and pedestrian specifically – at least not to any level of detail. Clewlow’s work and others documents avoiding parking and drunk driving for TNC use in urban areas as opposed to driving.
- Modeling gap: Travel modelers ignore parking cost, time, and hassle for the most part – assuming a trip starts when a driver enters a car, and ends when the driver depart. Survey of leading cities treatment of parking with respect to mode choice and travel behavior is targeted in early FY19.

Conclusions

This task advances understanding of the current state of urban data and mobility models along with city goals and priorities in the smart cities-energy-mobility space. City data infrastructure and mobility modeling are enabling analysis and ongoing evolutions in exploring emerging mobility technology services to travel behaviors related to vehicle automation, connectivity, electrification, and sharing. Overall key takeaways from data collection, analyses, and smart city analyses include an increased need to:

- Provide a typology across cities to inventory, integrate, visualize, and map 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 methods to observe transitions in impacts resulting from emerging ACES mobility technology, and influences in Mobility Energy Productivity.

- Address specific knowledge and data gaps as critical early-stage research; of particular need is to explore impacts and inform cities and national level understanding at the intersection of mobility and energy.

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. This task continues to develop and integrate transportation data infrastructure and modeling scenarios across cities to enable new technical analysis informing finalist's city and enabling continued collaboration as relevant to energy-efficient mobility and key research questions (listed below), of interest to advancing energy efficient mobility systems across cities, regions, and nationally, and to support economic growth, creation of new jobs, providing 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.

Next steps include:

- Identifying data/key uncertainties for state of art models/scenarios
- Co-developing MaaS behavioral economic models extended at airports + cities
- A Journal article that fills key knowledge gaps
- Optimization of MaaS/EVs/AVs for Urban / District services -focus on commuting

Key Publications

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3. Schaller, Bruce. The New Automobility: Lyft, Uber and the Future of American Cities. 2018. <http://www.schallerconsult.com/rideservices/index.html>

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V.2 Mobility Energy Productivity Metric (NREL) [Task 2.1.2]

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Project Funding (FY18): \$770,000	DOE share: \$770,000	Non-DOE share: \$0

Project Introduction

The Energy Efficient Mobility Systems (EEMS) program conducts research to identify and develop system-level transportation technologies and innovations that enable an increase in mobility energy productivity. While energy can be objectively measured (in terms of fuel consumption, emissions, etc.), the concept of accessibility/mobility is more difficult to quantify as it is heavily context-based. Addressing this need, a first-of-its-kind, high-resolution, comprehensive mobility energy productivity (MEP) metric has been developed by NREL. The MEP metric is defined by quantity and quality of goods, services and employment that people can access efficiently reach (with respect to time, cost and energy across any mode of travel). Derived from accessibility theory, the MEP metric advances practice by using readily available travel time data combined with established parameters that reflect the energy intensity and affordability of various travel modes, and relative frequency of activity engagement. The MEP metric is being developed with an aim to compare alternative futures related to technology, infrastructure investment (based on outputs from travel models), providing a much needed decision support tool for transportation planners, researchers, and analysts.

Objectives

- Develop and test a comprehensive metric that reflects energy productivity, affordability and accessibility of current and future mobility services
- Develop a MEP calculation module that can be integrated into travel demand models in order to accurately capture the primary as well as secondary impacts of various scenarios on mobility of a region

Approach

- Conduct a comprehensive literature review on existing metrics that quantify accessibility/mobility and identify theories that help develop a comprehensive MEP metric
- Collect travel time, land use, and energy productivity related data for multiple cities in the United States
- Develop the MEP metric and carry out a comparative analysis across different cities (subset of 7 smart city finalists) and scenarios (AMDs, TNC mode shares, CAVs penetration)
- Work with DOE labs to gain a thorough understanding of the input/output structures of BEAM and POLARIS models and develop a tight-knit workflow to take the output of either of these models as input for MEP calculation.

Results

From a comprehensive literature review conducted on existing accessibility/energy metrics, two key drawbacks were identified.

- The academic literature on transportation efficiency metrics is rich in theory but oftentimes limited by data availability and computational burden for widespread application.
- In contrast, popular industry metrics that have become readily available (and even popular with consumers) are mode specific and proprietary, limiting their ability to obtain a comprehensive picture of mobility of a region.

The literature review has revealed the necessity for a comprehensive (including all modes), integrated (including accessibility, and energy efficiency of travel), open source (available for use free of cost), and data agnostic (can make use of readily available data sources) metric that can be applied at any geographical scale to quantify the quality of mobility.

An initial version of the MEP methodology (titled MEP 1.0) was developed and shared with DOE leadership. The preliminary results from applying the MEP methodology in Columbus, OH were submitted for presentation and publication at the Transportation Research Board Annual Meeting to be held in Washington DC. A brief overview of the initial iteration of the MEP methodology is presented below:

Travel Time-Weighted Cumulative Opportunities

The MEP metric calculation starts with computing a cumulative opportunity measure (Wachs and Kumagai, 1973; Vickerman, 1974) to quantify accessibility, by counting the number of opportunities that can be accessed within a certain travel time threshold. Cumulative opportunity measures (for each mode and activity type) are calculated for each 1 sq.km pixel (within a city or region of interest) for different travel time thresholds. The cut-offs for travel time thresholds are user defined. Let $o_{ijk t}$ denote the number of opportunities of activity j that can be accessed by mode k within the travel time threshold t from the i th pixel. As opportunities that are nearby can be accessed easier than the ones that are farther away, a negative exponential weighting factor is used to penalize the opportunities that are farther away. The travel time-weighted cumulative opportunities, O_{ijk} , are calculated as following:

$$O_{ijk} = \sum_t (o_{ijk t} - o_{ijk(t-10)}) \cdot e^{\beta t} \quad (1)$$

where β is the travel time decay factor (set to be -0.08 in this study), following Owen and Levinson (2014). Future efforts will explore the sensitivity of cumulative opportunities measure with varying values of the weighting factor β .

Energy-Weighted Mobility

One of the key facets of the MEP metric that sets it apart from existing accessibility metrics is accounting for energy efficiency of access to opportunities by different modes of travel. For example, a variety of opportunities can be accessed within ten minutes of travel by car, when compared to 10 minutes of travel by transit. However, the energy efficiency (from a fuel consumption and emissions perspective) of access to opportunities provided by car is lesser than that of the energy efficiency of access to opportunities provided by transit. Given the same travel time threshold, the opportunities that can be reached by more energy efficient modes such as walking, biking, and transit, are assigned a greater weight, while the opportunities that can be reached by less energy efficient modes, such as driving. A negative exponential weighting factor is used to average the travel time-weighted cumulative opportunities O_{ijk} across all transportation modes. Thus, the energy-weighted mobility for activity j at i th pixel, a_{ij} , is formulated as below.

$$a_{ij} = \sum_k O_{ijk} \cdot e^{\alpha(E_k / \min E_k)} \quad (2)$$

where α is the adjusting factor and equals to -0.3 based on engineering judgement, and E_k is the energy use per passenger-mile for transportation mode k . The energy-weighted mobility, a_{ij} , is then normalized to the scale of 0 to 100 score within each activity type by applying the min-max normalization technique.

$$z_i = \frac{x_i - \min(X)}{\max(X) - \min(X)} \times 100 \quad (3)$$

where X is the original array data $\{x_1, x_2, \dots, x_n\}$ and z_i is the normalized value of x_i .

Activity Frequency (and Energy) Weighted Mobility

The previous calculation provides an energy-weighted mobility score for each activity type at any given location. In order to provide a comprehensive metric, the score needs to be averaged by the frequency of activity participation. For example, work can be considered as a more regular activity than going to the bank or going shopping. To reflect this, scores are weighted by frequency of activity engagement across all activity types (data obtained from 2009 National Household Travel Survey). The final MEP metric for the i th pixel, M_i , is calculated as

$$M_i = \frac{\sum_j a_{ij} f_j}{\sum_j f_j} \quad (4)$$

where f_j is the trip frequency of activity. Figure V.2.1 below shows MEP metric applied to Columbus, OH.

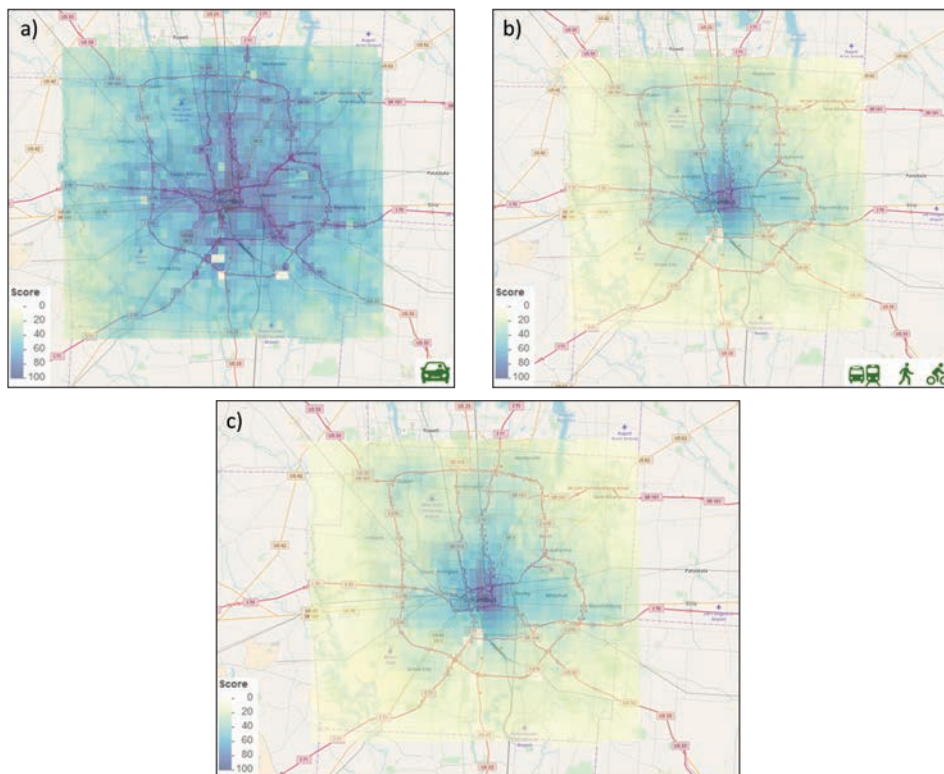


Figure V.2.1 MEP metrics for Columbus, OH for: a) Car mode; b) Walk, Bike, and Transit modes (combined); c) All modes

Based on the feedback from DOE leadership, the following key issues were identified in the methodology of MEP 1.0.

- **Scaling:** Scaling between 0-100 limited MEP 1.0's ability to accurately depict improvements in MEP

- **Affordability:** MEP 1.0 is not weighted with cost/mile usage of different modes
- **Inclusion of Additional Modes:** MEP 1.0 includes 4 modes namely walk, bike, transit, and car. Additional modes (such as TNCs, and Paratransit) were suggested for inclusion in future iterations of the metric
- **Spatial Aggregation:** MEP 1.0 is developed as a location based metric at the resolution of 1 sq. km for Columbus, OH. It is suggested that an appropriate spatial aggregation mechanism be identified to calculate a single MEP score for a city

The project team is currently addressing these issues and continues to enhance the metric. Figure V.2.2 shows an intermediate version of the metric (addressing scaling, affordability, and additional mode issues, along with a few methodological changes) applied to Austin, TX; Columbus, OH, and Denver, CO.

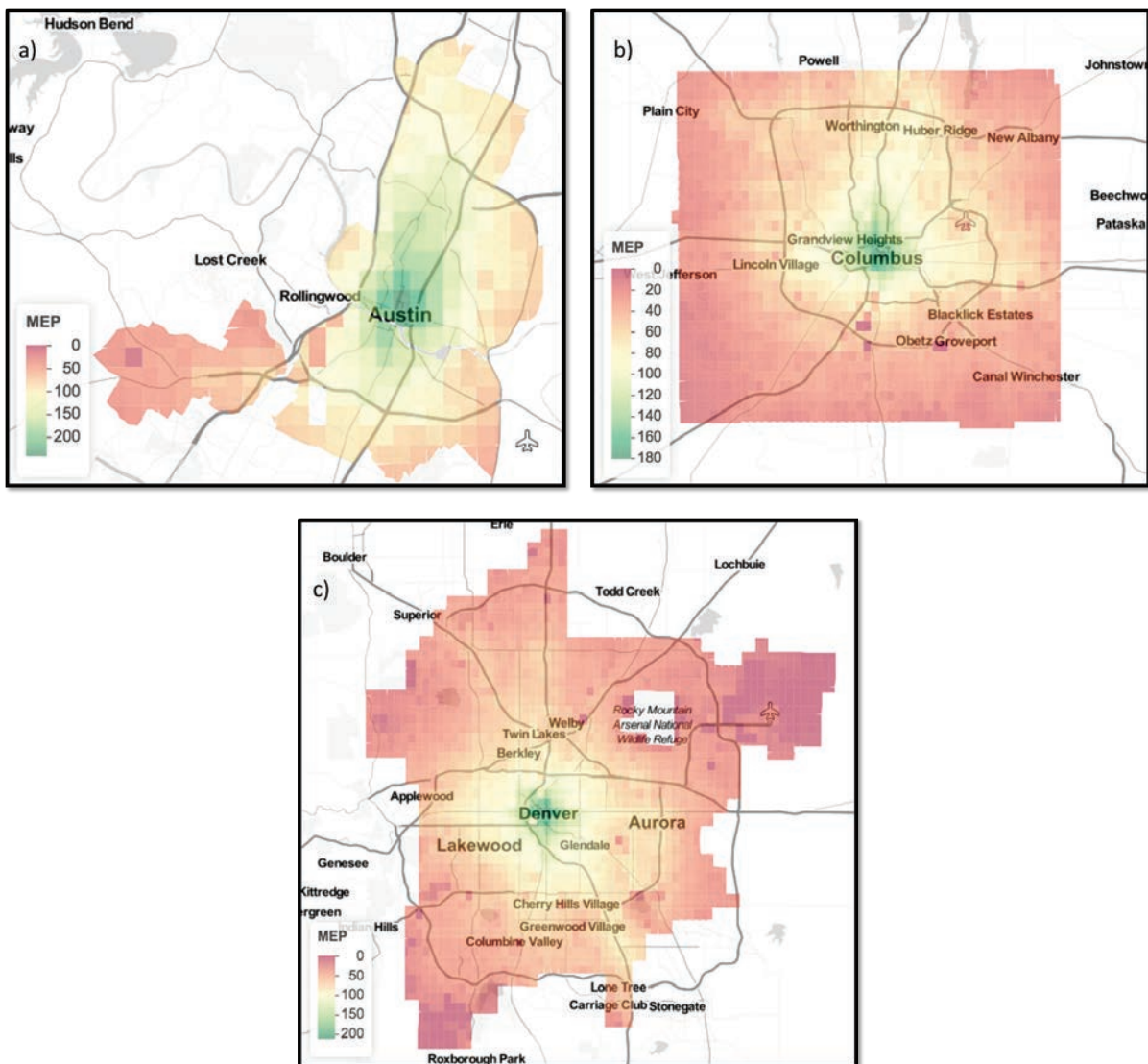


Figure V.2.2 MEP 2.0 methodology applied to: a) Austin, TX; b) Columbus, OH; c) Denver, CO

Conclusions

- The MEP metric is well received both within the DOE lab ecosystem as well as the broader transportation and energy research community
- The metric is being utilized to quantify the impact of various scenario runs being carried out as a part of the DOE SMART Mobility Consortium research
- The project continues to advance at a rapid pace with the following goals for FY2019
 - Final version of the metric by end of first quarter in FY 2019.
 - Development of a standalone MEP computation module
 - Extend the application of standalone MEP methodology to top 50 metropolitan cities in the US

Key Publications

1. Nag, Ambarish., Yi Hou., Venu M. Garikapati, and Stan E. Young. Literature Review on Accessibility Metrics. Working Paper: National Renewable Energy Laboratory (2018).
2. Hou, Yi, Venu M. Garikapati, Ambarish Nag, Stan E. Young, and Tom Grushka. A Novel and Practical Method to Quantify the Quality of Mobility: The Mobility Energy Productivity Score. Submitted for Publication to Transportation Research Record (2018).

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1. Owen, Andrew, and David M. Levinson. "Access Across America: Transit 2014 Data." (2014).
2. Vickerman, Roger W. "Accessibility, attraction, and potential: a review of some concepts and their use in determining mobility." *Environment and Planning A* 6, no. 6 (1974): 675-691.
3. Wachs, Martin, and T. Gordon Kumagai. "Physical accessibility as a social indicator." *Socio-Economic Planning Sciences* 7, no. 5 (1973): 437-456.

Acknowledgements

From the PI:

- The PI would like to acknowledge the wonderful project team (Yi Hou, Ambarish Nag, Jinghui Wang, and Tom Grushka) for all their diligent efforts in the development of this metric.

From the project team:

- Sincere thanks go to Dr. Stan Young (SMART Consortium Urban Science Pillar Lead) for his guidance on the development of this metric.
- The project team would like to extend their sincere thanks to the DOE leadership (David Anderson; Michael Berube; Stephen Chalk) for their regular feedback on the development of this metric.
- The team would also like to acknowledge their gratitude to Joshua Auld (Argonne National Lab), and Colin Sheppard (Lawrence Berkeley National Lab) for their constant feedback on the metric development and guidance in integrating the MEP metric with POLARIS and BEAM models.

V.3 SMART Mobility Modeling for Typical Mid-Size City [Task 2.1.3] (NREL)

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DOE share: \$175,000

Non-DOE share: \$0

Project Introduction

Agencies are increasingly expected to evaluate a variety of strategies suitable to accommodate long-term visions and day-to-day demand variability and to increase system reliability with feasible scenarios pertaining to planning and management of operations posing challenges at varying degrees based on their complexity, diversity and timeframe for implementation. Compounding their efforts are the emerging technological advances and “mobile revolution” we are experiencing which are disrupting travel behavior by providing personalized and contextually relevant traveler mobility options and information. Mobility options such as shared-use, electric vehicles, micro-transit, connected and autonomous vehicles and dynamic (real-time) information are already or expected to be part of the daily activities in the near-future, but their effect on the overall transportation system is not yet evident.

Autonomous vehicles could provide first and last mile accessibility to transit services negating the need for park-n-ride facilities (AV pilot deployments are under way in various states including Texas) or completely change mode choices with user preferences shifting to Shared Autonomous Vehicles (SAV) from traditional transit services, as indicated in recent modeling research from the University of Texas at Austin⁹. In addition to the system changes, technology and data are influencing and supporting traveler behavior, with disseminating information transitioning from static to dynamic with mobile platforms leveraging personalization, behavior, and system goals to deliver temporally, spatially, and contextually relevant mobility options to the user. Federal Highway Administration’s (FHWA) Active Transportation Demand Management (ATDM) program embraces tools and platforms that manage travelers behavior in real-time to achieve operational objectives. The notion of dynamically managing traveler behavior across the trip chain is the ultimate vision of ATDM¹⁰. A partner in this project, Metropia¹¹ utilizes a platform, powered by proprietary algorithms, data analytics and behavioral economics, is an example of such a multidimensional ADM framework (route, departure time and mode). As such, cities around the US are fully engaged in developing reports and plans that could provide a blueprint to prioritize investments and better understand what the impacts on travel behavior and system operations may be. The City of Columbus has grouped recommended activities under three (3) overarching themes named Enabling Technologies, Enhanced Human Services and Emerging Technologies, while the City of Austin has grouped recommended actions under five (5) areas named Shared-Use Mobility Services,

⁹ Jun Liu, Kara M. Kockelman, Patrick M. Boesch & Francesco Ciari, Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation.

¹⁰ Meenakshy Vasudevan and Karl Wunderlich, Analysis, Modeling, and Simulation (AMS) Testbed Preliminary Evaluation Plan for Active Transportation and Demand Management (ATDM) Program, November 2013.

¹¹ www.metropia.com

Autonomous Vehicles, Electric Vehicles & Infrastructure, Data & Technology and Land-Use & Infrastructure. The challenge the transportation agencies are facing is balancing the evaluation of transportation related strategies, policies and projects based on what they have been accustomed to while also incorporating elements that are on the horizon but where knowledge of their impact is limited or unknown.

These competing needs have placed emphasis in exploring advances in transportation modeling to develop, for analysis purposes, a robust, sophisticated and practical framework supporting the ultimate goal of providing an efficient, safe and sustainable transportation system for both passenger and goods movement.

Objectives

This project aims to:

- Bring new data and modeling methods related to Mobility as a Service (TNCs, Car-Sharing, Ride-Sharing & other), automated vehicles and other emerging mobility choices that will extend existing travel demand models and be transferrable to additional cities and regions.
- Highlight considerations for development and implementation approaches for employer provided mobility, AMD special generator and/or TNC use

Mobility options such as shared-use, electric vehicles, micro-transit, connected and autonomous vehicles and dynamic (real-time) information are already or expected to be part of the daily activities in the near-future, but their effect on the overall transportation system is not yet evident. For example, the use of electric vehicles is expected to reduce energy intensity, but the increase of connected vehicles may or not reduce congestion unless there is a dedicated lane¹². Similarly, autonomous vehicles could provide first and last mile accessibility to transit services negating the need for park-n-ride facilities (AV pilot deployments are under way in various states including Texas) or completely change mode choices with user preferences shifting to Shared Autonomous Vehicles (SAV) from traditional transit services, as indicated in recent modeling research from the University of Texas at Austin¹³. In addition to the technological advances on the supply side, the opportunity facing us today is making demand management more robust by leveraging technology, psychology, personalization, system goals, and institutional readiness to overcome barriers inhibiting discovering and selecting a new and efficient mode not used before. As such, cities around the US are fully engaged in developing reports and plans that could provide a blueprint to prioritize investments and better understand what the impacts on travel behavior and system operations may be.

Approach

The approach for this project includes:

- Working directly with a mid-size case city and technical partners using existing travel demand model and associated data.
- Extending model incrementally to include impacts of SMART Mobility, documenting methods with existing DTA with conventional trip generation practice.
- Estimating mobility & energy impacts of ACES within an existing / established modeling framework as a case study for other cities.

The two cities of focus, Austin TX and Columbus OH are sites of actively emergent new mobility technologies. The City of Columbus has grouped recommended activities under three (3) overarching themes

¹² Modeling the Impacts of Automated and Connected Vehicles in a Complex Congested Urban Setting, Texas A&M Transportation Institute, September 2016.

¹³ Jun Liu, Kara M. Kockelman, Patrick M. Boesch & Francesco Ciari, Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation.

named Enabling Technologies, Enhanced Human Services and Emerging Technologies, while the City of Austin has grouped recommended actions under five (5) areas named Shared-Use Mobility Services, Autonomous Vehicles, Electric Vehicles & Infrastructure, Data & Technology and Land-Use & Infrastructure..

In the context of SMART Mobility, exploring advances in transportation modeling to develop a robust, sophisticated and practical framework enhance d is a pre-requisite in order to better manage and predict transportation operations, and to integrate the flexibility to include future options as they appear.

Each city acknowledges the limitations of available city and regional models and anticipates expanding current modeling capabilities to include new transportation technologies and practices. The past year has shown growing developments in mobility as a service (MaaS) in the focus cities and nationally, as well as new practices, such as employer-provided mobility, and a reexamination of parking and curb space practices.

Results

Overview: Austin, TX

City agencies affiliated with transportation, housing, and business development in Austin have taken on leadership roles in shaping the future of transportation in the city. The Pecan Street development is actively experimenting with deployments of MaaS first/last mile shuttle service connecting users to transit stations within a focused area, concentrating on providing better access to transit from adjacent residential areas. The Pecan Street development is also a unique opportunity for modeling and experimentation, with a high concentration of EV owners who are engaged with data collection efforts. In addition to leveraging advances on the supply side, Austin is making demand management more robust by leveraging technology to discover and engage on efficient mobility options. The Central Texas Regional Mobility Authority (CTRMA) deployed Metropia's platform to manage demand during the construction of the Express Lanes on the Mopac Expressway. Metropia's platform, powered by AI-based algorithms, data analytics and behavioral economics, provides a multidimensional demand management framework to support transportation system congestion-management strategies and policies.

Austin is also committed to providing improved mobility options to low-income communities and to providing access to employment. The employer-provided mobility concept that has emerged in other places, notably in the Seattle area and in Silicon Valley, is a potential model for implementation in Austin. The research team will continue to explore how employer-provided mobility options could contribute to improved mobility access, with the capacity to reduce energy expenditure.

The research team has also developed recommendations for the CAMPO travel demand model development to balance the desire for a robust set of models with the need to have a set of models that fit within the region's strategy and plans for travel demand analyses as a whole. Minimally, enhancement recommendations bring sensitivity for Smart Mobility trends of CAV/SAV, TNC and automated mobility districts to multiple components of the CAMPO travel models. At the next level, recommendations would result in sensitivity among multiple components both on an individual basis and through linkages among components. Ultimately, a change of the entire CAMPO model structure to an integrated Activity-Based Model (ABM) and Dynamic Traffic Assignment (DTA) framework would create sensitivity that is even more fundamental.

Overview: Columbus, OH

The Smart City Columbus team has been highly engaged with city agencies and collaborative local and regional partners, aiming to support the rapidly developing integration of emerging technologies. During the past year, Columbus has conducted surveys to assess the state of adoption and adoption potential for electric vehicles in the city, targeting early adopters within the general public and transportation network company (TNC) drivers. Columbus leaders have identified the need to have better modeling capabilities to understand electric vehicle (EV) charging needs in order to develop infrastructure to support increased purchasing and use of EVs.

In addition, Columbus is poised to be an early testbed for implementation of automated vehicles (AVs), in particular, automated shuttle vehicles in a public downtown circulator system, and at least one large campus-based employer who is interested in automated shuttles.

Employer-provided mobility is of keen interest in Columbus, with at least one large employer running a pilot program for employees. The impetus for the employer is to reduce the need to expand car parking capacity to accommodate new employees, and to recruit and retain young, highly skilled employees, many of whom are not interested in owning a car and the associated costs.

Similar to Austin, the City of Columbus is exploring to leverage technology to offer citizens new mobility options. Recently the City of Columbus in partnership with COTA (the regional transit agency), prepared a Concept of Operations (ConOPs) plan outlining the development of the Multimodal Trip Planning Application (MMTPA) and Common Payment 190 System (CPS) and they issued a Request of Proposal (RFP) for the development of the MMTPA. As part of this RFP, a number of required characteristics were identified for the MMTPA including incorporating Artificial Intelligence (AI) and incentives.

This modeling framework currently in place for the City of Columbus was supported by a SHRP C10 grant and is based on ODOT's 3C MORPC ABM and Metropia's DynusT/DynuStudio DTA platform. The ABM component incorporates a number of advanced core demand models which when combined with the unique features of the DynusT/DynuStudio platform could be viewed as a transitional step to an Agent-based modeling and simulation (ABMS) framework.

Common to both cities

Both Columbus and Austin are high-profile innovation locations in terms of transportation technologies. The stature of these cities as drivers of new technological implementation is important, as they are mid-sized intercoastal cities that share characteristics with a wide range of similar U.S. cities. What is learned in these locations may be translated and applied in other locations. In each case, the city leadership and stakeholders in city agencies are well aware of their position and ability to shape and inform other cities. Both are strong collaborative partners who want to improve modeling approaches in order to more accurately reflect new modes, whether increasing numbers of EVs, AVs, e-scooters, or other technologies still over the horizon. The willingness to partner with SMART Mobility researchers is a valuable asset, through which several key emergent modes can be explored during FY2019.

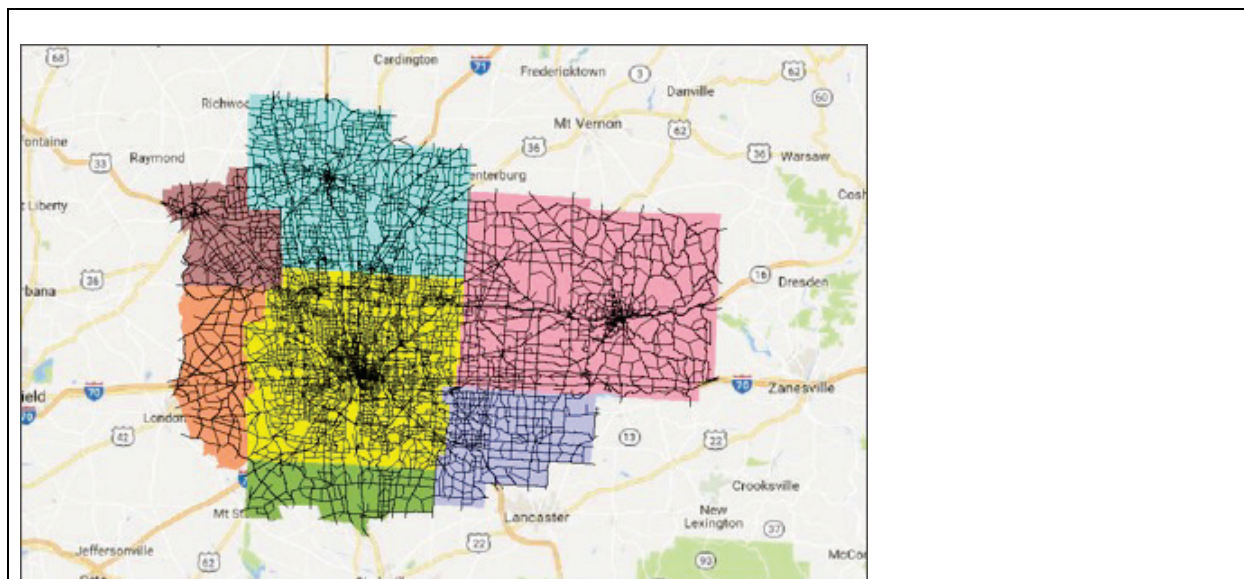
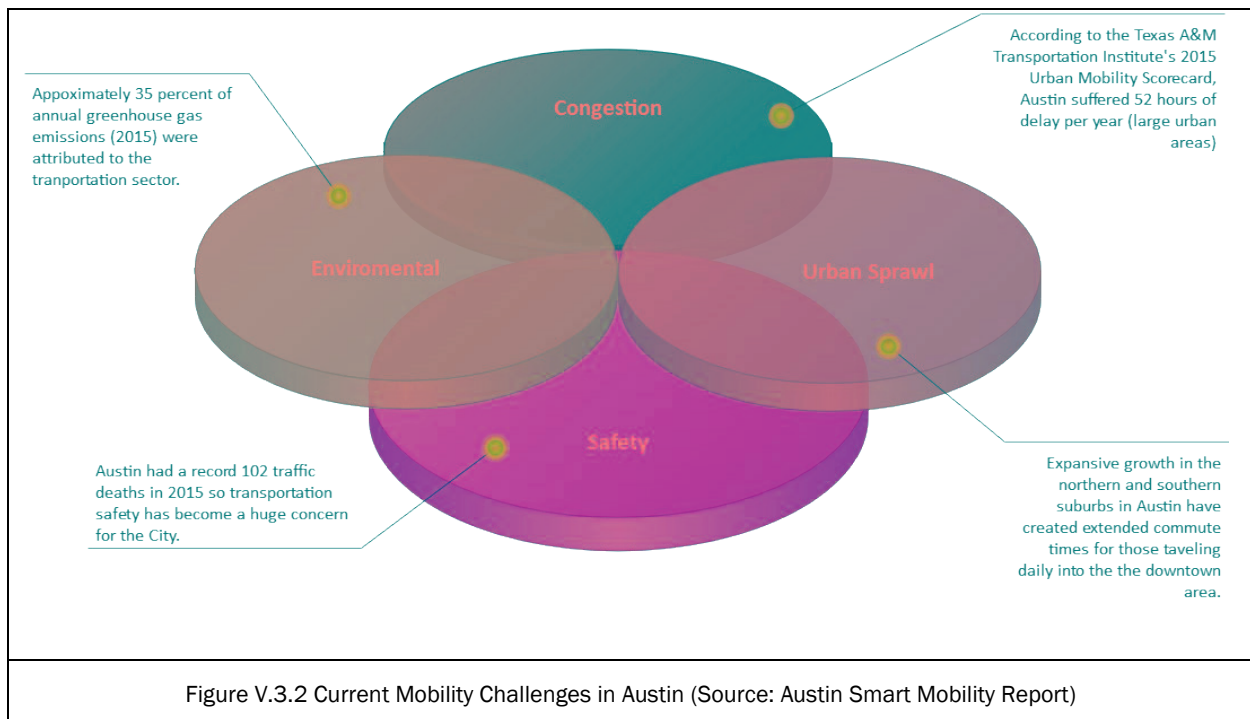


Figure V.3.1 ODOT/MORPC ABM-DTA Modeled Network (Source: Ohio Department of Transportation)



Conclusions

Both cities of focus, Columbus and Austin, are at the forefront of implementation of emerging transportation technologies and practices, and each is actively working toward improving the capabilities to model traffic flows. City staff are engaged in attempting to provide a better picture of the impacts of rapidly changing practices in order to more accurately anticipate the future of mobility. Continued interaction and collaboration with these cities is likely to further identify strategies in how best to inform similar cities facing many of the same challenges, and to contribute toward building a foundation of transferring findings from SMART Mobility efforts to practitioners who can use outcomes to improve practices.

The ongoing objectives of this task are to integrate findings from the cities of focus to:

- Enable reuse and augmentation of existing calibrated models within cities, extended to capture SMART technology impact of such things as: AMD, TNCs, Employer Provided Mobility and others.
- Provide case study for additional Smart Cities (with similar model maturity as case city) to capture energy and mobility impacts of various SMART models

Key Publications

Deliverable 5.1:

1. Austin Data and Modeling Environment Report
2. Columbus Transportation and Modeling Report

Deliverable 5.2: Smart Mobility Austin – CAMPO Model Capabilities and Enhancements

Deliverable 5.3: Brief Project Forum Report

References

1. Jun Liu, Kara M. Kockelman, Patrick M. Boesch & Francesco Ciari, Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation.
2. Meenakshy Vasudevan and Karl Wunderlich, Analysis, Modeling, and Simulation (AMS) Testbed Preliminary Evaluation Plan for Active Transportation and Demand Management (ATDM) Program, November 2013.
3. Modeling the Impacts of Automated and Connected Vehicles in a Complex Congested Urban Setting, Texas A&M Transportation Institute, September 2016.
4. Jun Liu, Kara M. Kockelman, Patrick M. Boesch & Francesco Ciari, Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation.

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V.4 Coupling Land Use Models and Network Flow Models (LBL) [Task 2.2.2]

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Project Funding (FY18): \$230,000	DOE share: \$230,000	Non-DOE share: \$0

Project Introduction

Conceptually the purpose of this project is to provide travel demand and traffic modelers – both within the SMART Mobility Consortium as well as in the transportation technology research community at large – with a more defensible point of departure for studying scenarios of future mobility. Most of the vehicle technologies studied by the Consortium are years if not decades away from fruition, and it is not realistic to expect the rest of society to sit idly by in the meantime. Any credible attempt to model the impact of future mobility technology must take into account the changes in land use, demographics, and real estate markets that are sure to have significantly altered our urban landscapes by the time the first fully electrified fleet of CAVs hits the road.

Integrated urban models of transportation and land use have long been the gold standard of regional planning, yet in practice would be more aptly described as the Holy Grail or philosopher's stone -- rarely, if ever, seen in person. Many planning agencies who claim to have an integrated model are simply handing off the results of 30-year land use forecasts to their travel modelers and calling it good enough. The trouble with this approach is that interdependencies between transportation and land use exist in both directions, and yet play out on vastly different time scales. The goal of Task 2.2.2 is therefore to extend current state-of-the-art land use models to allow for tight coupling with travel models and properly account for closed-loop feedback effects.

Objectives

The specific objectives of Task 2.2.2 are as follows:

- Extend UrbanSim with a travel model to allow for closed-loop feedback in simulation of land-use/urban infrastructure
- Build fast models for key variables such as vehicle ownership, workplace choice, time of day, and mode for mandatory activities (work and school), etc.
- Decrease computation time for extended UrbanSim using HPC or cloud resources in order to focus efforts on land use dynamics
- Develop 30-year scenarios for cities in portfolio (e.g. SF, CMAP, DRCOG) and plan for executing travel model integration at scale
- Run cloud scaled network flow model at metropolitan scale integrated with a long-term urban simulation model.

Approach

Our approach involves 5 main sub-tasks:

1. *Extend UrbanSim with a travel model to allow for closed-loop feedback in simulation of land-use/urban infrastructure.*

UrbanSim is an open-source microsimulation platform used by metropolitan planning organizations worldwide for modeling the growth and development of cities over long (~30 year) time horizons. It is a stable and mature technology yet represents a state-of-the-art approach to land use modeling, and therefore serves as the basis for most of the work in this project.

Currently, UrbanSim is often used by travel modelers to generate land use inputs for their modeling scenarios. For example, to estimate a model of travel demand in the year 2040, a modeler would first run an UrbanSim simulation out to the year 2040 and then use these static outputs as the starting point for their travel model. This one-way coupling completely disregards the way in which travel demand and land use are known to co-evolve.

Our aim is to develop a modular software architecture for a tight, closed-loop coupling between UrbanSim and a variety of different travel models whether they be agent based, four-step, or otherwise. The tight coupling would be based on a series of automated handoffs between the inputs and outputs of the land use, activity demand, and traffic assignment (TA) models, occurring during intermediate iterations of a given iteration. An UrbanSim simulation typically uses iterations of 1 or 5 years. For a year 2040 scenario with a base year of 2015, then, the tightly coupled travel model might get triggered at the end of each simulation year for a total of 25 cycles, or every five years for a total of 5 cycles (Figure V.4.1), and so on.

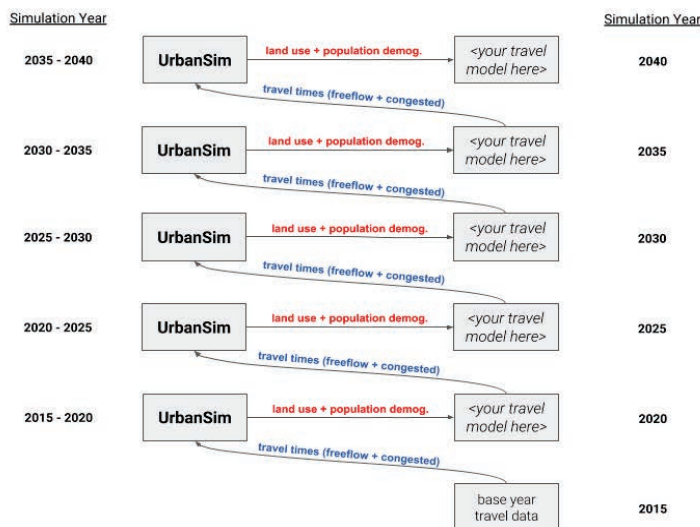


Figure V.4.1 Schematic of tightly coupled land use and travel models using 5-year cycles.

2. *Build fast models for key variables such as vehicle ownership, workplace choice, time of day, and mode for mandatory activities (work and school), etc.*

ActivitySim is an agent-based modeling (ABM) platform for modeling travel demand. It is built on much of the same open source code base as UrbanSim and therefore provides a natural linkage for closing the gap between our land use models and TA scenarios. In our proposed integrated modeling workflow, these lightweight activity models are adjusted by the urban dynamics models at a yearly time scale, providing the OD travel demand data for the network flow algorithms and TA. ActivitySim is under active development by a consortium of MPOs, transportation engineers, and other industry practitioners, with an official 1.0 release scheduled for 2018. Our work here will primarily involve

thoroughly calibrating, validating, and benchmarking ActivitySim in its current state, and developing a workflow for integrating its operation with UrbanSim outputs and TA inputs.

3. *Decrease computation time for extended UrbanSim using HPC or cloud resources in order to focus efforts on land use dynamics.*

In our tests, a single UrbanSim iteration for a synthetic population of 2.6M households and 6.9M individuals completed in just under 11 minutes of wall clock time on a Ubuntu Linux machine with 24 Intel Xeon X5690 3.47GHz CPUs. Extrapolating to the typical 30-year scenario, a complete UrbanSim run will take 5.5 hours using one-year intervals or 1.1 hours using a five-year interval. Many/most travel models take orders of magnitude longer than this to generate travel demand and solve a single day's worth of TA. It is likely that these steps will be the limiting factors in terms of the temporal granularity at which we can integrate land use and travel models. Thus we intend to focus our efforts on exploring the use of HPC and/or distributed cloud infrastructure to achieve the computational performance required to run 30 year scenarios in an "integrated" way.

4. *Develop 30-year scenarios for cities in portfolio (e.g. SF, CMAP, DRCOG) and plan for executing travel model integration at scale.*

Together with our travel modeling colleagues we will develop a suite of scenarios. The scenarios will be designed to meet the stated goals of the SMART Consortium, as well as to provide us with a method for assessing the impact of a tightly integrated modeling workflow relative to one-way integrations or completely un-integrated models.

5. *Run cloud scaled network flow model at metropolitan scale integrated with a long-term urban simulation model.*

We aim to leverage the results of the HPC/cloud-enabled network flow model described above to achieve a preliminary implementation of a tightly coupled simulation platform for modeling land use and transportation changes over 30-year time horizons.

Results

The key results from our FY18 work are as follows:

UrbanSim templates

We extended and abstracted the UrbanSim modeling framework around a modular design that we call model "templates". The template based structure enables the modeler(s) to maintain a single microsimulation instance or environment while allowing individual models or sub-components of a modeling workflow to be swapped in/out or substituted with those developed by other groups or researchers working in tandem.

Activity demand

We identified ActivitySim and its underdeveloped and underperforming models as the biggest obstacle preventing the closed-loop integration of land use and travel models. These models include workplace location choice, school location choice, auto-ownership, mode choice, mandatory + discretionary trip generation, and trip scheduling. We completed the process of overhauling the long term choice models like workplace and school location choice and have incorporated them into UrbanSim proper, resulting in dramatically improved runtimes (~16x). We have begun development on a codebase we are calling ActivitySynth to re-implement the remaining ActivitySim models necessary for generating activity demand. We completed a first pass of generating a full day's worth of OD trips and departure times based on the outputs of our household location choice, workplace location choice, auto-ownership, and primary mode choice models. We developed a workflow and data schema for passing these OD trips between UrbanSim/ActivitySynth and BEAM and are working to automate this process.

Traffic Assignment

We tested a static user equilibrium (SUE)-based traffic assignment algorithm on our tertiary network of 31,000 edges and 66,000 nodes. Performance was good enough that we opted not to implement on HPC in order to be

able scale up on cloud infrastructure in the future. We have continued the development of our GPU-based traffic microsimulation, both as a benchmark against the SUE approach as well as a novel solution for fast traffic assignment in its own right. We identified a major bottleneck in the traffic microsimulation in its implementation of Johnson’s all-pairs shortest path algorithm, and began a phase of benchmarking it against other algorithms, including our SUE implementation.

Integrated simulations

As noted above, computational constraints and incompleteness of the ActivitySim model prevented full end-to-end simulation of scenarios. However, we were able to run each component and manually pass the outputs from one to the other. Computational performance bottlenecks and algorithm limitations were clearly identified and used to motivate the key tasks proposed for FY19.

Conclusions

In FY18 we achieved the following:

- A thorough evaluation of existing activity demand generation technologies through experimentation and benchmarking
- Identification of underperforming or otherwise weak linkages preventing the closed-loop integration of land use and travel models, including workplace location choice, auto-ownership, mode choice, mandatory + discretionary trip generation and scheduling.
- Development of a modular software architecture (Figure V.4.2) capable of accommodating a) the integration of UrbanSim with a variety of different travel models; and b) the continued innovation of the individual sub-models determined during our evaluation phase to be underperforming.

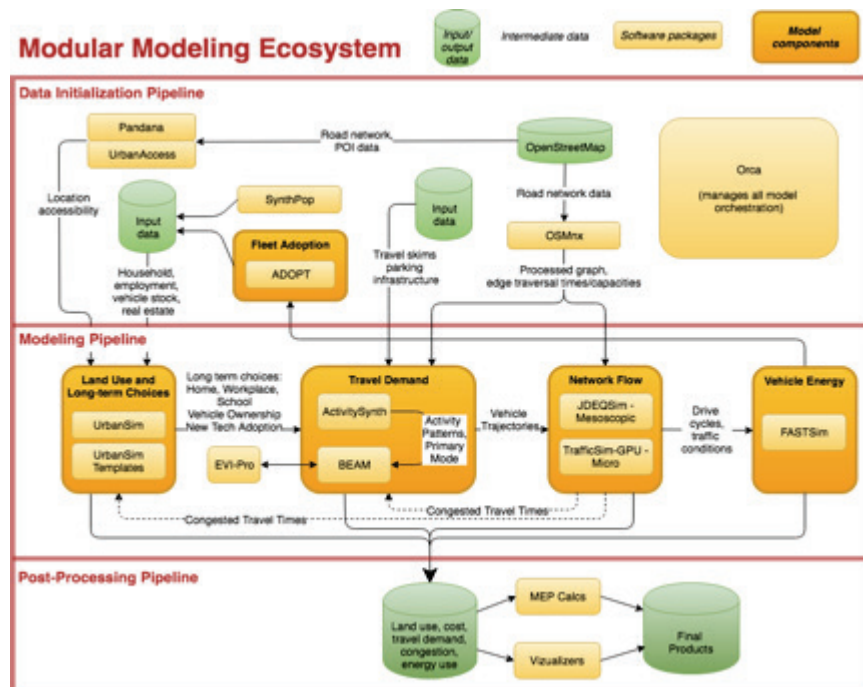


Figure V.4.2

Key Publications

1. Waddell, Paul, et al. "Architecture for Modular Microsimulation of Real Estate Markets and Transportation." arXiv preprint arXiv:1807.01148 (2018). Presented at the Symposium on Applied Urban Modelling. Cambridge, England. June 27–29, 2018.
2. Waddell, Paul, et al. "Urban Modeling Without Zones: A Metropolitan Graph-Based Microsimulation of Real Estate Markets and Transportation". Presented at the American Collegiate Schools of Planning Annual Conference in Buffalo, New York. October 25, 2018

V.5 Resilience for Electrified Vehicles and Automated Mobility Districts (LANL, INL) [Task 2.2.3]

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Project Introduction

Automated mobility is becoming a reality as new technologies emerge to provide automated vehicles and associated infrastructure. The ability to respond to unanticipated events is an important aspect of developing and maintaining engineered systems that may be subject to unexpected disruptions that can disable or degrade system performance. In support of the anticipated deployment of automated mobility systems, we examine resilience concepts and propose an approach for characterizing and understanding resilience. While we focused our initial study on simple closed-loop systems, our approach enables development of concepts, models, and analyses that can be extended to more general situations. A modeling approach, Statistical Planning for Resilience in Next Generation Systems (SPRINGS), is proposed to provide tools for resilience assessment. The SPRINGS resilience modeling approach is intended to support distributional analyses of a variety of mobility systems and associated infrastructure ranging from specific automated transit systems such as closed loop trolley systems to associated infrastructure such as charging stations for electric vehicles.

Objectives

The overall objective of Task 2.3.3 is to develop a statistical approach for resilience of Smart City technologies such as Electric Vehicles (EV), Automated Vehicles (AV), and Connected Vehicles (CV) that can be used to explore the distributional behavior of systems under normal, stressed, and extreme conditions. This task incorporates expertise in statistical analysis and modeling, socio-technological analysis of infrastructure disruptions, and modeling and simulation of transportation systems. Resilience assessment should address the need for robust systems that can respond to abnormal and extreme conditions such as large public events, disasters, and evacuations and which can address the needs of citizens, including underserved populations. Ultimately, this approach is intended to aid planning and mitigation actions to address extreme conditions such as special events, natural disasters, and other emergency situations.

Specific goals that were established include the following:

- Use socio-technological principles to develop a conceptual model.
- Investigate statistical methods for characterizing distributional behavior of systems under normal, stressed, and extreme conditions.
- Model impact of disruptions to normal operating conditions and resilience of system response as abnormal conditions subside.
- Model the resilience of charging systems for electrified vehicles and transportations services in AMDs.
- Demonstrate use of resilience modeling to enable development of systems that can respond quickly to unusual or unanticipated events.

Approach

The SPRINGS approach involves development of a conceptual model, development and application of statistical methods for characterizing systems under normal, stressed, and extreme conditions, and demonstration of these methods using simulated data.

Resilience is increasingly recognized as a key factor in the ability to maintain functionality of complex, critical infrastructure systems in the face of a range of possible attacks, natural disaster impacts, and anomalous travel scenarios, such as mass evacuations (Sims 2011). We define resilience as *the resistant characteristics and adaptive capacities of a system that enable it to respond to disruption with lower probability of failure, shorter time to recovery, and/or reduced level of negative impacts* (Sims and Brelsford 2011). As this definition suggests, resilience encompasses multiple related phenomena, including the ability of a system to resist any impact whatsoever from a disturbance, the ability of a system to adapt and reconfigure in order to maintain full functionality during a disturbance, and how quickly a system can recover following a disruption that actually does degrade its functionality (see Holling 1996). The scope of analysis of resilience also varies, from inherent resilient capacities of a system in isolation, to multi-system views that encompass repair services, organizational capacities, and economic resources (Cox et al. 2011).

Researchers have proposed a variety of ways of breaking down these multiple aspects of resilience. For example, Bruneau et al. (2003), in a formulation that has been widely cited, describe resilience in terms of “4 Rs”: *robustness*, the “strength” or ability of a system to resist breakdown; *rapidity*, the speed with which functionality can be restored after a breakdown occurs; *redundancy*, the degree to which components of the system can substitute for one another; and *resourcefulness*, the capacity of social systems to set priorities, make decisions, and mobilize resources in non-standard ways. In a similar formulation, Cox et al. (2011), following work by ecologist C.S. Holling (2001) describe resilience in terms of *vulnerability*, analogous to robustness above; *availability of resources* to respond to change; and *flexibility*, or ability to control and reconfigure elements of a system.

These aspects of resilience suggest a number of strategies that might be applied to transportation systems to increase their resiliency, including:

- *Adding redundancy*, for example by building networks that afford multiple access paths to each node.
- *Maintaining excess capacity*, for example by keeping a reserve stock of vehicles on hand to respond to unusual circumstances
- *Adding flexibility*, for example by incorporating on-demand transportation solutions that enable system reconfiguration on the fly without disruption to passenger access (see Cox et al. 2011 and Madni and Jackson 2009 for additional examples).

These strategies each have strengths and weaknesses in relation to different modes of transportation system disruption, including:

- *Point failures*, such as removal of isolated tracks, road segments, or stations from service
- *Global capacity degradation*, for example from a snow storm that reduces vehicle speed across an entire transportation system
- *Demand surges*, for example from large numbers of people trying to get to or evacuate from a particular area
- *Logistical failures*, such as breakdowns in control systems that optimize vehicle flow through a transportation system

These failure modes and resilience strategies suggest a number of different scenarios that we can use as a basis for modeling and assessing resilience of transportation systems.

There are a number of considerations that are important for understanding resilience for Smart Mobility Systems. Autonomous/adaptive transportation systems will have fewer fixed elements in their operating configurations. This makes it more difficult to define a single optimal operational state, and provides many more control options, although in practice centralized control may become more difficult. Although these systems may have the potential to be far more resilient than conventional transit systems, they also create challenges for analysis and control that could negatively affect system resilience (see Perrow 1999).

The current stock of private vehicles sits unused between trips, representing a huge excess vehicle capacity that is assumed to be available for exceptional situations like evacuations. (Although lack of ownership of private vehicles is increasingly recognized as a barrier to evacuation, and road capacity becomes a constraint at some point.) A completely on-demand transportation system could theoretically operate much closer to its maximum capacity, leaving limited excess capacity in the system to respond to exceptional circumstances.

The most efficient smart transportation systems may be those that combine traditional, fixed-configuration transit systems, such as light rail, with flexible, on-demand feeder systems such as shared-ride vans. In order to model these systems, it may be necessary to draw on and integrate existing modeling approaches and data sets that cover private vehicle traffic, taxi and ride-sharing services, and traditional transit systems.

There are numerous examples of closed-loop mobility systems. Situations where this type of system is used include the Dallas Fort Worth Airport SkyLink train that connects different terminals and gates, the airport rental car shuttle system at the Albuquerque Sunport, and various university campus bus systems. Our work is motivated in part by the Kansas City Trolley system which consists of a 2 mile Trolley Track with 16 stops. Another example of a downtown closed-loop system is the Detroit People Mover, a 3 mile single track system with 13 stops.

To provide a mathematical environment for studying resilience, we developed a trolley simulation based on a simplified mathematical representation that includes selected attributes of a mobility system that can be used to investigate resilience properties. We define a simple closed-loop mobility system S as a set of vehicles V_i that move along a simple closed path P consisting of a series of n stops. Transit occurs as a vehicle moves along a route on the path from one stop to the next. Movement along the route can be represented as travel along a connected path in either a uni-directional or bi-directional manner, with the different segments being associated with either deterministic or random travel times. More simply, the travel can be viewed as a series of transitions, where a transition is associated with movement from a given stop s_i to an adjacent stop s_j .

Our simulation modeling approach involves generating distributions of riders and travel segments or transitions, and potentially other quantities that can impact the resilience of a mobility system. The number of

riders can be modeled using the Poisson distribution which has a parameter λ corresponding to the number of events in a specified time interval.

Travel times can be modeled with various distributions, such as the log-normal which concentrates most of the distribution in a focused area but allows for a long right tail corresponding to infrequent long travel times. To avoid unrealistically long values, truncated versions of distributions can be invoked.

Wait times are determined by the arrival rates of riders at each of the stops as well as the travel times between stops. The distributions of the riders and travel times will induce a distribution on the wait times.

A variety of metrics can be defined for quantifying various aspects of resilience. For example, various summary statistics (mean, median, standard deviation, min, max) can be calculated to examine the location and dispersion of system variables. Some quantities that might be of interest include the total number of passengers on board available vehicle(s), total number of passengers waiting, number of passengers waiting at individual stations, and average wait time across the system. One might also take a more comprehensive approach and look at the waiting time distributions at individual stops rather than focusing on averages. Various summary statistics can be used individually or combined into user-defined quantities that attempt to capture system performance measures important to resilience assessment, such as Average Wait Time/Target Wait Time, Average Queue Length/Car Capacity, etc. In addition, it is important to consider sources of uncertainty throughout the modeling process and how these uncertainties can propagate and impact decision-making.

A simulation was developed using the mathematical framework described above for a simple closed-loop trolley system with one 50-passenger trolley car and 5 stops. For simplicity, rather than having distributions of travel times, equal time steps were used to represent movement of the trolley between stops. Riders were drawn from Poisson distributions with varying values for the parameter λ to generate different distributions of passengers entering and exiting the system at the different stops.

The simulation begins by initializing the system with 0 riders on the trolley and empty queues at each of the stops. As the simulation begins, the number of riders at each stop is drawn from a Poisson distribution with a λ value specific to that stop. At each time step, new passengers arrive at each stop and line up to board the trolley. Passengers in the queue at the stop where the trolley car is located are allowed to board until the car is filled. The trolley car then advances to the next stop, allows a stop-specific Poisson generated sample of riders to exit and then allows new passengers from the queue at the current stop to board. The trolley car proceeds around the loop dropping off passengers and picking up new passengers up to the trolley car capacity. By running the simulation over a period of many steps, we are able to examine the ability of the system to handle the passenger loads arriving at the different stops.

The simulation allows tracking of the progress of the simulation over time as the 50-passenger trolley car picks up and drops off passengers. Simulation outputs provide the number of passengers in the trolley car as well as the number of passengers waiting at each stop at a series of time steps. Varying the capacity of the trolley car provides system information in the presence of hanging system behavior.

With a 50-passenger trolley car, the car frequently fills up and passengers are left standing in their queues for multiple circuits of the trolley car. As the size of the car is increased, the ability of the trolley system to handle the passenger load improves. With a 60-passenger trolley car, the system only fills to capacity occasionally, while the 70-passenger trolley car is generally able to accommodate all passengers. A variety of diagnostic plots can be generated to investigate the distributional behavior system-wide as well as at individual stops.

Histograms of the trolley car load and queue lengths are generated at the individual stops across the simulation for 50-, 60-, and 70-passenger trolley cars. These plots give a sense of the distributional attributes associated with the varying capacity trolley cars.

Once a simulated system or a model of real data is available, a variety of studies are possible in which factors such as the passenger flow can be altered at the different stations simultaneously or at varying rates over time. If there is an unexpected increase in the passenger flow, a system can become overloaded, similar to the situation that arose with the 50-passenger trolley car simulation. If the flow increases beyond system capacity, the system will eventually be overwhelmed. Once the flow decreases, the system should be able to return to normal conditions. The rate at which the system recovers is one aspect of resiliency.

The quantitative process for resilience assessment based on the trolley simulation described above led to the development of a set of metrics and distributional summary statistics to address different aspects of resilience, such as the location and dispersion of system variables and calculation of combined quantities important to the particular system under study.

Results

Implementation of the approach described above led to the following results:

- Specification of a conceptual foundation for resilience assessment that integrates socio-technological modeling concepts with mathematical rigor
- Development of the SPRINGS model based on statistical distributions to characterize and assess normal, stressed, and extreme conditions
- Exploration and identification of potential data sources
- Construction of a simulation for simple closed loop systems to enable development of resilience assessment methodology.
- Implementation of resilience concepts for simulated data
- Development of metrics and techniques for quantifying different aspects of resilience

Results were documented and disseminated in a variety of venues including a project report, programmatic progress and review presentations, and poster presentations at two professional conferences. A research manuscript is in preparation. Further details may be found in the Key References Section.

Conclusions

This project has developed a statistical approach, SPRINGS, for characterizing resilience. The approach has been demonstrated for a simulated closed-loop transit simulation inspired by the Kansas City Streetcar. Future research on the mathematical methods would draw upon statistical concepts from extreme value theory, mixture models, computer experiments, and integration of heterogeneous data. Further development of this approach would be enhanced by collaborative interactions with experts in specific aspects of mobility such as transportation network companies, charging infrastructure, and dynamic systems models for adoption of automated mobility technologies. Ultimately, this approach would enable timely analysis and characterization of resilience, and proactive planning for mobility systems and associated infrastructure that can respond to changing conditions and return to normal operation as quickly as possible. Our approach is intended to encourage active probing of systems and examination of flows as different interventions are introduced, allowing the system manager the opportunity to experiment with different strategies and see the impacts on different variables and metrics associated with understanding resilience.

Key Publications

1. Wendelberger, Joanne and Sims, Benjamin, "A Preliminary Framework for Investigating Resilience," technical report, Los Alamos National Laboratory, LA-UR-18-21002.

2. Wendelberger, Joanne and Sims, Benjamin, “Resiliency Modeling for Automated Mobility,” Los Alamos National Laboratory, LA-UR-18-22441, poster presented at the Smart Cities Connect Conference, Kansas City, Missouri, March 26-29, 2018.
3. Wendelberger, Joanne and Sims, Benjamin, “Resilience for Electrified Vehicles and Automated Mobility Districts,” presentation for All-Pillar Call, March 27, 2018, Los Alamos National Laboratory, LA-UR-18-22557.
4. Wendelberger, Joanne and Sims, Benjamin, “Statistical Resilience Model - SPRINGS,” Los Alamos National Laboratory, LA-UR-18-23460, discussion of statistical resilience for the SMART Mobility Model Review held at Argonne National Laboratory, April 24-25, 2018.
5. Wendelberger, Joanne and Sims, Benjamin, “Resiliency Modeling for Automated Mobility,” Los Alamos National Laboratory, LA-UR-18-22441, poster presented at the Joint Research Conference on Statistics in Quality, Industry, and Technology, June 11-14, Santa Fe, New Mexico.
6. Wendelberger, Joanne and Sims, Benjamin, “Resiliency Analysis for Automated Mobility Systems,” Los Alamos National Laboratory, LA-UR-18-23459, poster presented at the 2018 EERE Vehicle Technologies Office Annual Merit Review, Arlington, VA, June 18-21.

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Acknowledgements

Project leadership wishes to acknowledge the following contributions to this project.

- Ben Sims, Los Alamos National Laboratory, contributed sociotechnological modeling expertise, development of the conceptual model, and co-authorship of several technical products.
- This project benefitted from regular discussions with the Urban Science Pillar team, headed by Stan Young, NREL.
- Interactions with Brian Bush and Laura Vimmerstedt, NREL, stimulated ideas on the application of resilience modeling to dynamic systems models and other computational systems.

- Bob Bennett, Chief Innovation Officer, Kansas City, Missouri, provided helpful perspectives on city infrastructure data that impacted our thinking on the closed loop transit system simulation inspired by the Kansas City Streetcar.

V.6 Infrastructure Spatial Sensing at Intersections (LIDAR) [Task 2.3.6] (NREL, ANL)

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End Date: September 30, 2018

Project Funding (FY18): \$70,000

DOE share: \$70,000

Non-DOE share: \$0

Project Introduction

This joint project between NREL and ANL aims to explore the mobility and energy impact potential of infrastructure spatial sensing (such as LiDAR) at critical intersections by enabling connected and automated vehicle (CAV) applications such as eco-approach and departure, reducing traffic accidents through increased safety, and obtaining vehicle dynamic data at higher resolution than was previously possible. The team has built a network of collaborators who are all pursuing this concept in parallel (the University of Nevada at Reno, Continental, MioVision, and the University of Tennessee at Chattanooga, to name a few). The University of Nevada at Reno (UNR) is collecting data live at an intersection using two overlapping LiDAR sensors, and directing the high-bandwidth sensor feed to their data processing research lab. ANL had developed a proof-of-concept portable awareness system, which is an exploratory platform with multiple sensors (LiDAR, infrared camera, and video) for spatial sensing data collection and future research. NREL is also researching and developing the energy equivalence of safety improvements and crash avoidance.

Objectives

- Assess the mobility/energy impact potential of spatial sensing (such as LIDAR, RADAR, and video/image processing) at critical intersections, through more efficient vehicle/signal coordination, greatly enhanced safety, and significantly strengthen observability of all modes and objects.
- Establish the energy equivalence of safety at signalized intersections.

Approach

- Work with partners to assess the maturity of existing LIDAR/RADAR/image technology (limits and future capabilities) to support roadside deployment, object detection, abstraction, and communication.
- Estimate the energy impact of foreseen enhancements on safety, such as the energy equivalency of improved safety from crash prevention, near-misses detection, and prevention.

Results

- Assess the maturity of existing infrastructure spatial sensing (LIDAR/RADAR/image) technology and partners from academia and industry. When NREL and ANL began this research at the beginning of year, the research team was aware of only two initiatives within industry to promote this concept, one with the University of Nevada, Reno, and the other with Continental Corp. Over the course of the past year, approaches to intersection spatial sensing has blossomed into several industry players, with initial deployments. The list of known activity is outlined below, most of which the research team is actively in communication with.
 - Academic
 - University of Nevada Reno [1], [2] (MOU with UNR is under legal process at NREL)
 - Sensor Manufacturers (specific to intersections)
 - MioVision (<https://miovision.com/>) [3]
 - GridSmart (<https://gridsmart.com/>)
 - Traffic Vision (<http://www.trafficvision.com/>)
 - System Integration / Demonstration
 - Continental – 2019 demonstration in Columbus [4]
 - Honda - 2018 Marysville, Ohio [5]
- Additionally, the research team under the leadership of ANL developed an exploratory portable awareness system using LiDAR, IR imagery and low-light camera
 - Argonne National Laboratory proof of concept exploratory portable awareness system and data collection
 - Platform with multiple various sensors (LiDAR, IR camera, etc.)
 - Exploratory for data collection

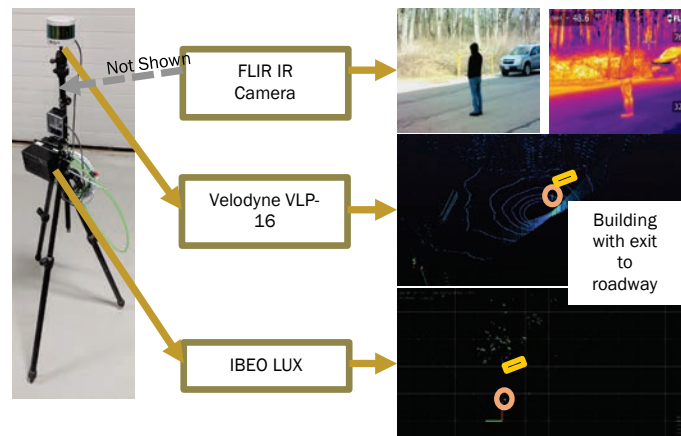


Figure V.6.1 Argonne National Laboratory proof of concept exploratory portable awareness system

Energy equivalency of improved safety: Intersections present some of the highest conflict zones and are thus highly represented in crash statistics. Improvements at intersections are motivated primarily by safety and mobility efficiency. The research team lead by NREL undertook an initiative to bring better understanding of the energy consequences of vehicle crashes, including fatal, injury and property-damage only. This paper, currently in draft, builds on previous work that estimates the economic impacts. This energy equivalency of safety paper (“Explore First Order Approximation of Energy Equivalence of Safety at Intersections”) was submitted to ASCE International Conference on Transportation & Development (ICTD 2019) and continues to be refined with collaborator input.

- Energy equivalence of safety at signalized intersections for direct impacts of each crash type:
 - Fatal crash equivalent cost of 87,459 gallons of gasoline
 - Injury crash equivalent cost 2,351 gallons of gasoline
 - PDO crash equivalent cost 388 gallons of gasoline

Details are illustrated in the table below (DRAFT)

Table V.6.1 Energy equivalence of safety summary – DRAFT ESTIMATES/RESULTS

All Roads			
	Fatal Collision	Injury Collision	PDO
# of crashes on all roads	30,296	2,969,963	10,565,514
# of person/vehicles on all roads (*)	32,999	8,504,771	18,508,632
Total direct cost (\$) (**)	\$ 46,163,000,000	\$ 124,344,000,000	\$71,480,000,000
Direct cost (\$) per crash	\$ 1,523,733	\$ 41,867	\$ 6,765
Direct GGE per crash	87,462	2,403	388
Total indirect cost (\$) (***)	\$ 255,646,000,000	\$ 338,159,000,000	\$ -
Indirect cost (\$) per crash	\$ 8,438,276	\$ 113,860	\$ -
Indirect GGE per crash	484,357	6,536	-
Total GGE per crash	571,819	8,939	388

Intersections			
# of person/vehicles of crashes	8,682	4,829,008	10,127,014
# of crashes equivalence	7,971	1,686,345	5,780,930
% of crashes at intersections	26%	57%	55%
Total direct cost (\$)	\$ 12,145,000,000	\$ 69,080,000,000	\$ 39,111,000,000
Direct cost (\$) per crash	\$ 1,523,678	\$ 40,964	\$ 6,766
Direct GGE per crash	87,459	2,351	388
Total indirect cost (\$)	\$ 67,261,000,000	\$ 183,717,000,000	\$ -
Indirect cost (\$) per crash	\$ 8,438,379	\$ 108,944	\$ -
Indirect GGE per crash	484,363	6,253	-
Total GGE per crash	571,822	8,604	388

- *: For fatal and injury collisions, # of people in crashes; for PDO, # of vehicles in crashes
- **: **Direct cost** includes medical expenses, legal and court costs, emergency service costs, insurance administration costs, congestion costs, property damage, losses of productivity, and workplace losses
- ***: **Indirect cost** means loss of quality-of-life
- Gasoline gallon equivalent (GGE) is used to equal the energy quantity of one liquid gallon of gasoline

Conclusions

- The maturity of existing infrastructure spatial sensing (LIDAR/RADAR/image) technology is quickly advancing, much faster than originally anticipated twelve months ago. Initial product offerings from at least two companies (MioVision and GridSmart) are showing initial capability. Partners and collaborators from academia and industry are publishing results. As an example, both University of Nevada, Reno and MioVision have classified ‘near-misses’ from their respect sensor suites, indicating ability to spatially assess position and movement of vehicles within field of view. More and more companies and universities/institutes are pouring resources into this area.
- Energy equivalency of improved safety: Just as a production vehicles have both direct (fuel expended) and indirect (included in life-cycle energy analysis) aspects of energy efficiency, so also vehicle crashes have both immediate impacts (delay and congestion), direct and long-lasting impacts (loss of work/productivity), as well as broader societal impact. Energy equivalence of safety at signalized intersections for each crash type have been estimated using economic studies as a basis. Although assumptions and equivalencies between economic parameters such and GDP and total US energy expenditure are first order estimated, nonetheless, even with large uncertainties, this analysis indicates that long term consequences from crashes related to loss of productivity are significant, dwarfing immediate concerns of congestion and delay. Gasoline gallon equivalent (GGE) is calculated by the national level GDP energy ratio (Conversion ratio = Total energy in BTUs expended during the year / National GDP) and then converting it from BTUs to GGE. The research team is currently consulting with economic and safety experts related to the validity of the assumptions and equivalencies used in this initial effort.

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1. Zhu, Lei, Stanley Young, “Explore First Order Approximation of Energy Equivalence of Safety at Intersections,” ASCE ICTD 2019. (IN DRAFT)

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V.7 Assessing Urban Impact: Automated Mobility Districts (NREL) [Task 2.4.1]

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Project Introduction

Connected and automated vehicles (CAVs) are increasingly being discussed as the basis for shared mobility and on-demand services to replace privately owned vehicles. The rapid growth of Transportation Networking Companies (TNCs) and their increasing investment in automated vehicle (AV) technologies attests to this. Combining the concepts of TNCs, with AV and on-demand transit services, the term “automated mobility district” (AMD) describes a district-scale implementation of CAV technology to realize the full benefits of a shared, fully automated vehicle service within a confined region. Figure V.7.1 presents a conceptual depiction of the AMD concept.

Objectives

- The primary objective of this task is to develop a modeling architecture to quantify the mobility and energy benefits of AMDs.
- In FY18 the focus was primarily on
 - Exploring various simulation packages that would serve the needs of AMD toolkit development
 - Developing intra-district AMD simulation capabilities
 - Reaching out to AMD deployment partners and soliciting data from field deployments
- The focus of FY19 efforts will be
 - Exercising the AMD toolkit to help inform operations in real-world AMD field tests
 - Development of a module for fleet and route optimization for AMD deployment
 - Integrating AMD toolkit with a regional model to assess inter-regional impacts of shared automated vehicles



Figure V.7.1 Conceptual depiction of AMDs

Approach

Model Description

The proposed automated mobility district (AMD) modeling and simulation toolkit builds on the Simulation of Urban Mobility (SUMO) —a microscopic traffic simulation suite, and integrates the Future Automotive Systems Technology Simulator FASTSim, a vehicle/powertrain simulation tool. In tandem, the toolkit is able to provide the AMD’s fuel/energy and mobility impacts of AMDs under various travel demand scenarios. The workflow of the AMD simulation toolkit is shown in Figure V.7.2

Using the AMD toolkit developed in FY18, experimental scenarios were tested with different combinations of operational variables to provide insights on energy and mobility gains that can be realized in AMDs.

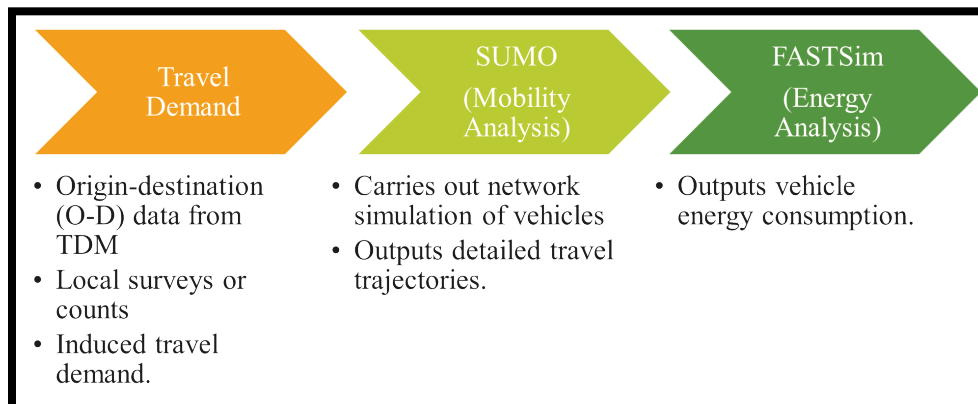


Figure V.7.2 AMD Toolkit – Workflow

A hypothetical network containing 13 nodes and 48 links is generated in SUMO to test several AMD deployment scenarios (shown in Figure V.7.3). Four Automated Electric Shuttle (AES) vehicles operate “on-demand” in the hypothetical AMD. This means an AES will be dispatched to pick up a passenger when a trip request is made by the passenger (analogous to most elevator controls). Once an AES is dispatched, it will pick up and drop off the passenger at the designated AES stop nearest to the traveler’s destination. The AES will then wait at that destination stop until another request is made for pickup by another traveler. Two AESs operate in the clockwise direction of the loop, while the other two serve the demand in the counter-clockwise direction. In this study, the AES seat capacity is one, which means each AES can only take one passenger at a time.

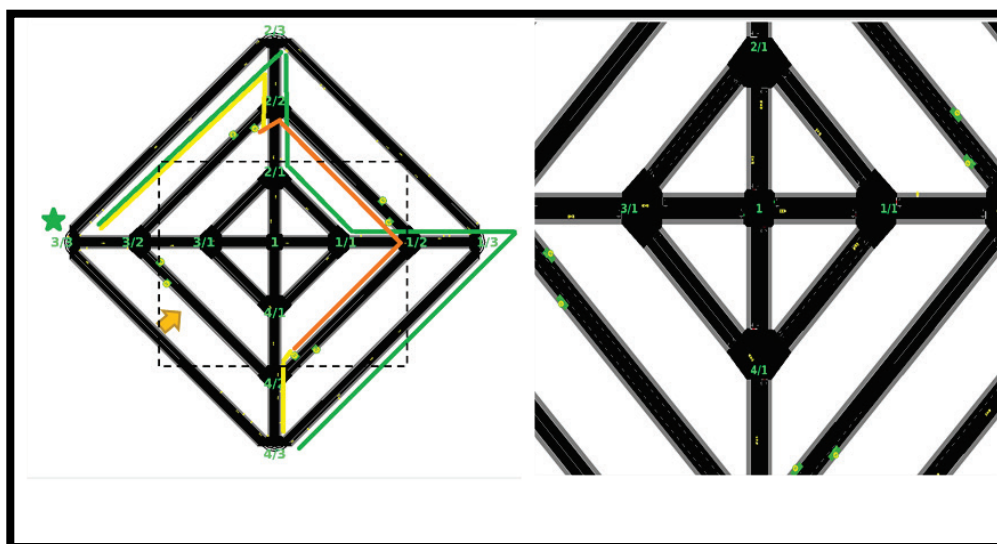


Figure V.7.3 (a) A hypothetical AMD network in SUMO and (b) A zoom in on the network to show signals, sidewalk lanes and vehicles. [Green lines → Car mode; Yellow lines → Pedestrian mode; Red lines → AES mode]

For the hypothetical network, simulation is carried out for a demand of 300 trips distributed across the 13 origin-destination (OD) pairs. Within this district simulation, all ODs are within feasible walkable distances, and the walk mode is for door-to-door trip completion. The choice set of travel modes encompasses 1)

passenger car, 2) AES, 3) walking. Traffic demand is distributed according to a bimodal distribution reflecting a morning and afternoon peak hour during a typical day.

Assumptions

The following assumptions were made for the preliminary AMD analysis:

Network: A hypothetical trapezoidal network (shown in Figure V.7.3) is generated in SUMO.

Travel Demand: The travel demand in the network is exogenous to the model (calculated or determined outside the simulation toolkit). For the preliminary analysis, hypothetical traffic demand is generated and distributed across the 13 origin-destination (O-D) pairs in the network.

Mode Share: This initial study intends to understand the mobility and energy impacts of an AMD, so the mode shares are “assumed” as shown in Table V.7.1. For a real-world AMD deployment, the mode shares would reflect observed data once the shuttles run for a few months in the field.

Table V.7.1 Travel Mode Share of All Scenarios

Scenarios	Car mode	Walk mode	Automated shuttle mode
Baseline	70%	30%	0%
Transitional	60%	20%	20%
Optimistic	50%	10%	40%

AES Fleet: A total of four automated electric shuttles serve the designated demand in the AMD. This is not a limiting factor for the analysis, and the number and seating capacity of shuttles can be increased to cater to additional demand as required.

Vehicle Characteristics: The characteristics of the privately driven cars in the simulation are set to match a standard midsize sedan such as the Toyota Camry. This was the most popular sedan by sales volume in the United States in the year 2016, and thus representative of an average car. This vehicle has an EPA-rated fuel economy of 25 MPG. For the automated shuttle, both a gasoline and an electric powertrain are considered. For simplicity, the 2016 Camry is also taken to represent the potential automated gasoline shuttle. The 2016 Nissan Leaf is selected to represent the performance of the potential automated electric shuttle.

Results

Simulation results for the three AMD scenario runs are illustrated in Table V.7.2.

Table V.7.2 The Simulation Results for AMD Network Performance.

Scenario	VMT (miles)	VATT (seconds)	VATD (miles)	FC (gal) [gasoline/ BEV shuttle case]
Baseline	128.8	86.5	0.6	5.9
Transitional	153.8	124.3	0.8	7.0/5.3
Optimistic	175.7	168.5	1.1	8.0/4.5

The reported performance metrics for the AMD include:

- Vehicle Miles Traveled (VMT)—the sum of all private vehicle and automated shuttle mileage for the scenario
- Vehicle Average Travel Time (VATT)—the average time of travel in vehicle, (does not include walking), averaged across private vehicles and automated shuttle trips
- Vehicle Average Travel Distance (VATD)—the average travel distance (excluding any pedestrian links), averaged across private vehicle and automated shuttle trips.
- Fuel Consumption (FC) in gallons of gasoline across the entire system.

From the table, it can be observed that compared to the baseline scenario, the transitional and optimistic scenarios exhibit an increase in VMT, VATT, and VATD. VMT of transitional and optimistic scenarios increase by about 19% and 36% respectively compared to baseline, which can be attributed to automated shuttles traveling to the departure stop to pick up a passenger (referred to as overheading), along with the assumed travel shifts from walking to automated shuttle mode. Additional empty vehicle deadheading after a passenger trip does not contribute to VMT in this analysis as the automated shuttles park at the passenger drop off location and wait there until summoned for the next trip. VATT and VATD also see an increase in transitional and optimistic scenarios, again due to overheading and reduced proportion of walking mode. For the gasoline automated shuttle case, total gasoline consumption increases along with total VMT, but for the AES case, the transitional and optimistic scenarios see fuel consumption decrease by 10% and 26% respectively.

Conclusions

As we move into the era of CAVs, vehicle electrification, and shared mobility in transportation, it is critical to identify and explore the optimal confluence of these technologies that maximize mobility while minimizing energy consumption. One such idea is that of AMDs which is a district-scale implementation of AV technology to realize the full benefits of an on-demand shared automated mobility service within a confined geographic region.

This year's efforts focused on developing an AMD modeling and simulation toolkit and reports on the preliminary analysis results for hypothetical AMD deployment, exercising the toolkit with three scenarios. The AMD toolkit is capable of simulating detailed vehicle movements for various operational configurations of automated shuttle services including fixed route, on-demand, and mixed services to quantify the mobility and

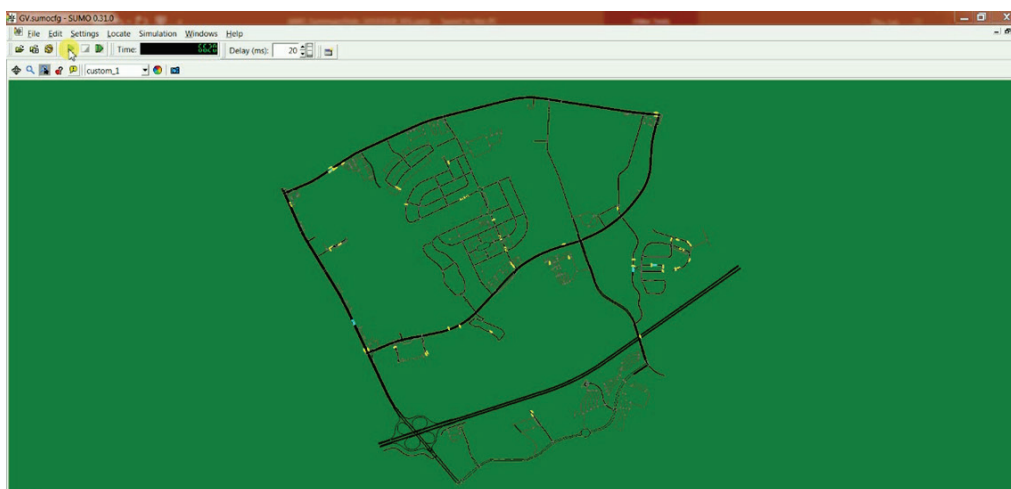


Figure V.7.4 A depiction of Greenville AMD network in SUMO

energy benefits of AMDs. Work is underway to incorporate the Greenville travel demand and network data into SUMO software in order to simulate and inform the operations in Greenville AMD deployments.

Future research will focus on enhancing the toolkit to integrate and implement different operational configurations of AMDs and define and quantify various performance metrics for AMDs, as well as for the traditional modes in the simulation (vehicles, pedestrians, as well as buses and other traditional mass transit).

Key Publications

1. Zhu, Lei, Venu Garikapati, Yuche Chen, Yi Hou, HM Abdul Aziz, and Stanley Young. "Quantifying the Mobility and Energy Benefits of Automated Mobility Districts Using Microscopic Traffic Simulation." In International Conference on Transportation and Development, p. 98. 2018. [Won Best Poster Award at the ASCE-ICTD 2018 conference]

Acknowledgements

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V.8 Smart urban signal infrastructure and control (ORNL, PNNL) [Task 4.1]

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Project Funding (FY18): \$310,000	DOE share: \$310,000	Non-DOE share: \$0

Project Focus in FY 2018

The advances in connected and automated vehicle technologies can be leveraged to efficiently control the signalized intersection in an urban environment. Connected and automated environment provides an unprecedented environment for traffic state observability in real-time and the connectivity among vehicles and infrastructure components such as signal controllers allow the development of data-driven traffic flow control schemes. Our focus in FY18 was to utilize the connectivity between vehicles and signal controllers, and the data sensing (e.g., Basic Safety Message—BSM and Signal Phase and Timing—SPaT) for developing signal control algorithms with mobility and energy goals. This is directly tied with the overarching goals of the project: (a) How will traffic signals and sensors shape command and control infrastructure to improve SMART mobility? (b) What are the potential gains—mobility and energy—from optimal sensing and control, increased observability from CAVs and improved sensor technology? Data-rich environment with connected vehicles provides an excellent avenue for executing machine learning based traffic control such as reinforcement learning (RL). RL-based techniques are well suited for dynamic environment like the road traffic networks. A major advantage can be gained in terms of computational complexity because no optimization is necessary in real-time. Further, we also approached the signal control problem from a stochastic distribution control theory perspective. The key idea is to use stochastic distribution control theory to develop signal timing control so that the traffic flow distribution over a concerned area as uniform as possible, this realizes smooth traffic flow over an urban area with minimized energy consumption. The input is the signal timing settings for an intersection, and the output is the probability density function (PDF) of the queue length. The controller uses the output queue length PDF as a feedback signal and compares it with the target PDF (which is narrowly distributed Gaussian with minimum mean value), using such an error and the control algorithm to obtain signal timing for the intersection.

Objectives for FY 2018

Our objectives for FY 2018 were: (a) to develop signal control algorithms that leverage the connectivity and data in an ACES environment to minimize energy consumption from urban signalized transportation networks, To execute the algorithms in a simulated environment of real-world signalized corridor and to demonstrate the energy reduction benefits, (b) to understand the impact of the market share of CAVs in a mixed traffic environment on the performance of the developed algorithms through sensitivity analysis, (c) to identify potential sensor technologies that enables the data and communication environment for real-world

implementation. These objectives will help us to provide an assessment of the impact of signal control optimization in an ACES environment in terms of energy minimization, and mobility improvement and to estimate the impact of CAV market-share on signal system performance.

Approach

Reinforcement learning based control:

We have developed reinforcement learning (RL) based algorithms where the signal controllers learn to optimize over time through observing the transition of traffic states resulting from exploring and exploiting controller settings such as adjusting phase sequences and green durations. The stochastic nature of traffic flow in a transportation network makes it particularly suitable for RL-based approach where the solution technique does not need any prior information on the system. Compared to actuated and adaptive control schemes, the solutions from a RL-based technique can be theoretically proven to be optimal. Further, we integrated energy goals into the control objective. Explicit energy minimization objectives are often discouraged in signal optimization algorithms due to its negative impact on mobility performance. One potential direction to solve this problem is to provide a balanced objective function to achieve desired mobility with minimized energy consumption. This research developed a RL-based control with reward functions considering energy and mobility in a joint manner--a penalty function is introduced for number of stops. Further, we proposed a clustering-based technique to make the state-space finite which is critical for a tractable implementation of the RL algorithm. An RL-based algorithm requires essential components--state, action, and reward--to be defined specific to the problem at hand. This research developed a decentralized architecture where each agent capable of controlling the traffic signal individually without any central supervising agent. Using vehicle to infrastructure (V2I) communication, an agent equipped with roadside unit (RSU) collects all the basic safety messages (BSM) from approaching equipped vehicles. Next, the agent collects information about the traffic states of neighboring intersections using infrastructure to infrastructure (I2I) communication. Finally, the agent determines state, action and rewards of the proposed RL algorithm and signal control decisions are made based on reward evaluations.

Stochastic distribution control:

Traffic flow modeling and control for one-signal corridor based on the stochastic distribution control theory are investigated to achieve smooth and uniform traffic flow distribution in the traffic network. In this context, we develop static and linear dynamic stochastic distribution traffic queue models to formulate probability density function of traffic queue. Stochastic distribution control algorithms are designed to control probability density function of traffic queue provided by the stochastic distribution traffic queue model such that it is as narrow and as left as possible. And, we propose a recursive input-output traffic queue model which is data-driven and dynamic in nature to calculate real-time traffic queue using traffic signal timings and loop-detector data. MATLAB-based simulations are conducted to support our traffic flow models and control algorithms. We developed a stochastic distribution traffic queue model and control for one-signal corridor. We describe our stochastic model in terms of probability density function of traffic queue as the output (*i.e.* traffic flow distribution) and ratio of green signal interval to total signal interval as the input (*i.e.* traffic signal timing). This stochastic model can use the real-time data generated by our input-output model so that it can work in real-time as well.

Results

Results from reinforcement learning based control:

We implemented the algorithm in a calibrated NG-SIM network within a traffic micro-simulator--PTV VISSIM. At first, the calibrated Lankershim Boulevard arterial was trained for 450 times using different random seeds. The simulation period for each of these runs was 15 minutes. The rewards and other performance metrics were obtained directly from VISSIM. Finally, the Q-table was updated after the implementation of the random action. After initial training of the Q-table, the authors explored the network for additional 50 runs, each having 15 minutes simulation period. Finally, the Q-table was updated based on the rewards obtained from VISSIM. We compared three strategies: A. control delay minimization, B. energy (fuel

consumption) minimization, C. Energy minimization with penalty for number of stops made by the vehicles. The developed RL algorithm with a flexible penalty function in the reward is expected to achieve desired energy goals for a network of signalized intersections without compromising on the mobility performance. The

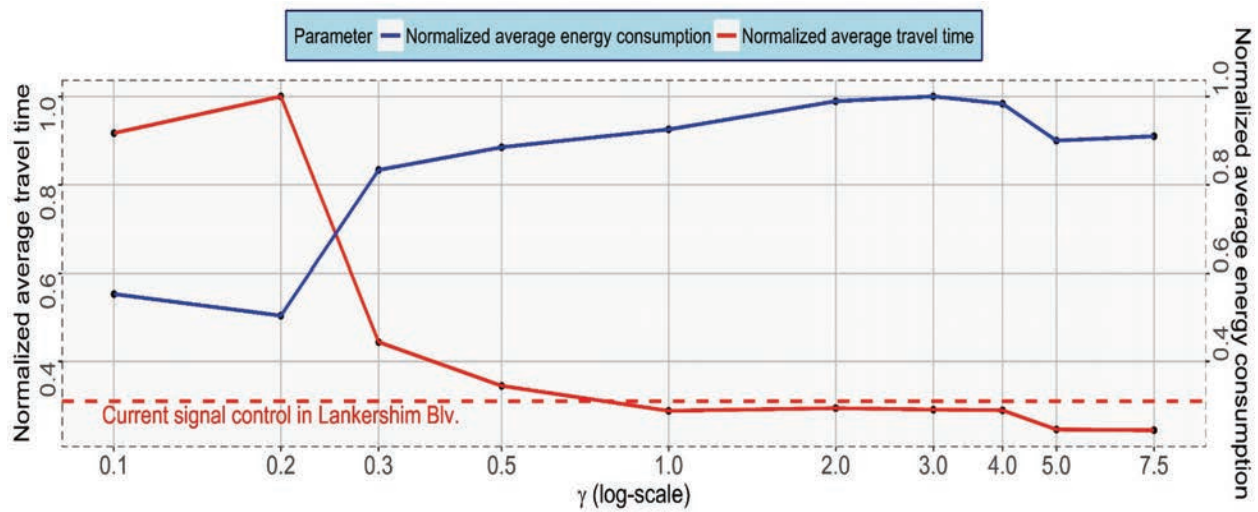


Figure V.8.1 Trade-off between Mobility and Energy for Different Penalty Values

normalized reward function is defined as: $R_{EC-DL} = R_{EC} - \Gamma(k) = R_{EC} - \mu \times \gamma \exp(\delta k)$. Where, R_{EC} = Energy consumption, $\Gamma(k)$: exponential penalty as a function of number of stops k . $\mu = 23.5$, $\gamma \in [0.1, 7.5]$, and $\delta = 0.0486$. Figure V.8.1 shows the trends of trade-off between mobility and energy performance metrics for the Lankershim Boulevard network. With higher value of γ , the mobility performance improves. Further, we conducted statistical tests to justify the findings using a sample of 33 VISSIM simulation instances each with a different random seed. The mean values of travel delay, stopped delay, travel time, system-level travel time, and number of stops are reported at 95% confidence interval assuming Student t distribution with unknown standard deviation for the tests. Figure V.8.1 reports the results and range of the metrics.

Table V.8.1 Statistical Verification of Results

Performance Metrics		Strategy-A	Strategy-B	Strategy-C
Average delay* (seconds)	Mean	42.47	81.97	59.58
	Range	$41.6 < \mu < 43.4$	$70.3 < \mu < 93.7$	$55.1 < \mu < 64.1$
Completed trips*	Mean	918.09	488.09	849.73
	Range	$912.6 < \mu < 923.6$	$451.5 < \mu < 524.7$	$833.7 < \mu < 865.8$
Number of stops**	Mean	1914.64	2332.64	2260.48
	Range	$1877.2 < \mu < 1952.1$	$2041.5 < \mu < 2623.8$	$2147.0 < \mu < 2373.9$
Average queue time** (seconds)	Mean	28.56	118.48	51.85
	Range	$27.9 < \mu < 29.3$	$108.2 < \mu < 128.8$	$46.9 < \mu < 56.8$
System travel time** (seconds)	Mean	73558.85	124355.56	95392.92
	Range	$72690.3 < \mu < 74427.4$	$119117.3 < \mu < 129593.8$	$90511.7 < \mu < 100274.1$
Fuel-cons** (gallons)	Mean	11.12	5.33	9.39
	Range	$11.0 < \mu < 11.3$	$4.9 < \mu < 5.72$	$9.2 < \mu < 9.5$

* for all the completed trips; **for all vehicles including the remaining vehicle in the network

Preliminary results from stochastic distribution control:

Based upon the stochastic control framework and using the equivalent transfer function model for the queue length with the input signal as the ratio of the green light for a fixed cycle case, a B-spline stochastic distribution model has been formulated using data generated from the transfer function model. Both static and dynamic models have been obtained and closed loop simulation for a single intersection has been carried out, where the purpose is to control the signal timing so that the probability density function (PDF) of the queue length (as a random process) is made to follow a target PDF shape. For the static model, an equivalent B-spline function model that approximates the queue length PDF has been obtained. For these purpose, 20 weights have been selected and their trained values are listed in the following table. These weights illustrate how the input signal timing (i.e., the green light ratio) is related to different degree of impact onto the queue length PDF [3], where for different input green signal period from 20 secs to 29 secs the corresponding row is the weights related to the B-spline function approximation.

Table V.8.2 The Weights Matrix for the Static B-spline Queue Length PDF Model

Weights for basis functions

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}	w_{11}	w_{12}	w_{13}	w_{14}	w_{15}	w_{16}	w_{17}	w_{18}	w_{19}	w_{20}
20	0	0	0	0	0	0	0	0.34	0.91	1.085	1.042	0.73	0.17	0.04	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0.04	0.13	0.73	1.43	0.99	0.78	0.17	0.04	0	0	0	0	0
22	0	0	0	0	0	0	0	0.08	0.34	1.04	0.95	1.21	0.52	0.13	0.04	0	0	0	0	0
23	0	0	0	0	0	0	0	0.08	0.47	0.69	1.17	1.12	0.56	0.21	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0.04	0.21	0.78	0.95	1.43	0.73	0.17	0	0	0	0	0	0
25	0	0	0	0	0	0	0.04	0.08	0.43	0.73	1.38	0.86	0.56	0.17	0.04	0	0	0	0	0
26	0	0	0	0	0	0	0.04	0.08	0.82	0.95	1.21	0.82	0.26	0.13	0	0	0	0	0	0
27	0	0	0	0	0	0	0.13	0.43	0.95	0.86	1.08	0.47	0.30	0.08	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0.26	0.69	1.30	1.12	0.69	0.17	0.08	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0.26	1.049	1.47	0.95	0.30	0.26	0.04	0	0	0	0	0

Using these weights to represent the queue length PDF for the static model, an optimal green light ratio has been obtained and used to control the signal timing at the concerned intersection. The simulated intersection on the approaching queue length PDF responses are given in Figure V.8.2, where the top figure shows the target

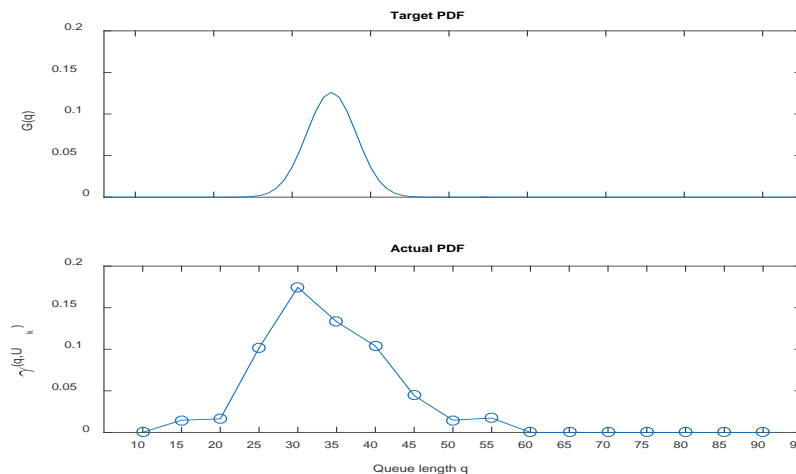


Figure V.8.2 Target and Actual Queue Length PDFs for Static B-spline Model Based Control

queue length PDF and the bottom figure gives the actually controlled queue length PDF. It can be seen that desired results have been obtained as the queue length PDFs are dynamically approach to a narrowly distributed uniform distribution along with the progress of the time. As for the dynamic B-spline model, the method in stochastic distribution control theory has been used to establish the required closed loop control algorithm and the closed loop simulation results are given in the following figure, where it can be seen again that a desired results have been obtained (More details can be found in [4]).

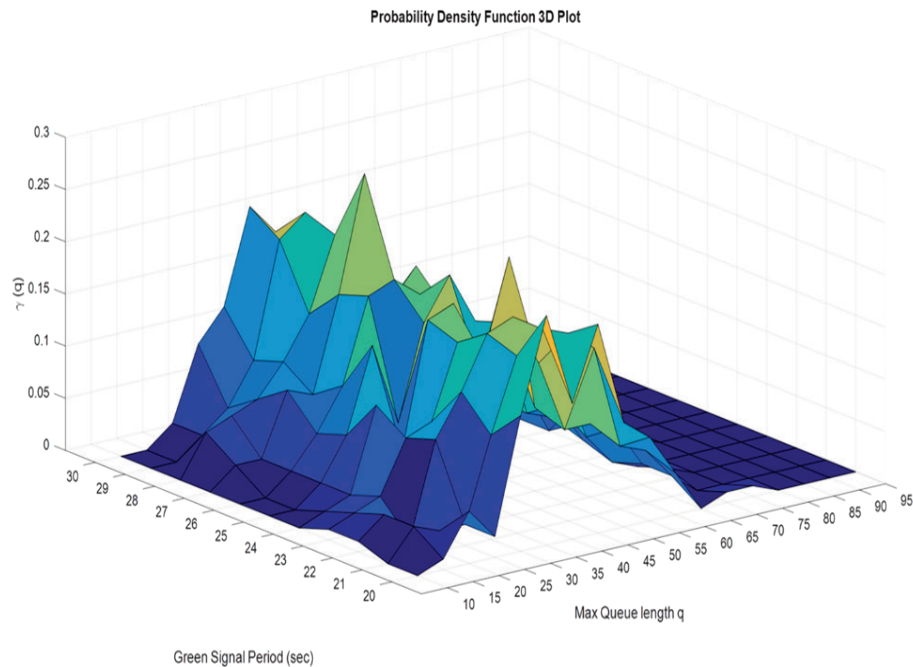


Figure V.8.3 Response Plot of the Queue Length Dynamics for a Single Intersection Control

Preliminary results for collaborative fault tolerant control for non-signalized intersection with 100 CAVs

Fault diagnosis and collaborative tolerant control has also been preliminarily developed for 100% CAVs penetration. Indeed, with the potential of increased penetration of connected autonomous vehicles (CAVs) in the future, intersectional signal control faces new challenges in terms of its operation and implementation. One possibility is to fully make use of the communication capabilities of CAVs so that intersectional signal control can be realized by CAVs alone – this leads to non-signalized intersection operation for traffic networks. In this part, the collaborative fault tolerance functionality has been developed at CAVs operational level in response to possible individual vehicle faults, where the research question is how other healthy CAVs can be

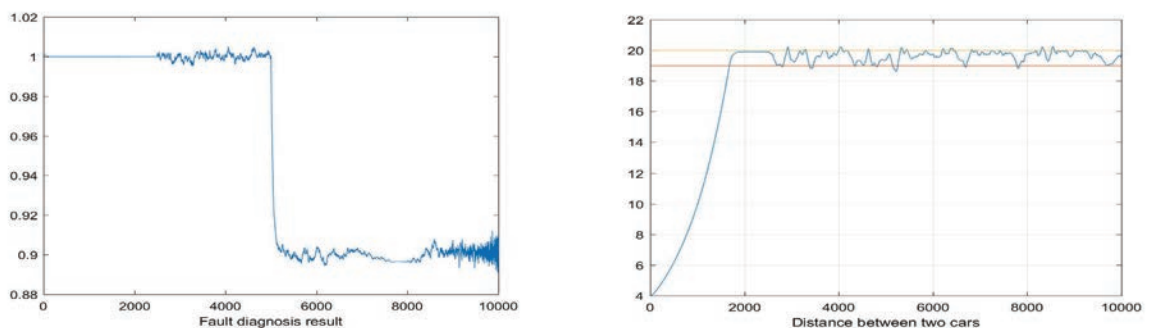


Figure V.8.4 Fault Diagnosis Results and the Guarantee of Safe Distance between Any Two CAVs

controlled to smoothly and safely pass through the concerned intersection when there is a fault a CAV. In this work, a detailed modeling using multi-agent-based approach has been formulated together with the construction of fast fault diagnosis and tolerant control algorithms. A nonlinear optimization problem has been formulated that can maximize the passing through speed of other healthy CAVs under a set of constraints on the minimum distance safety requirement. Figure V.8.4 show the preliminary results on single intersection collaborative fault tolerant control, where the desired fault diagnosis result has been obtained and the safe distance of any two CAVs can be always guaranteed during the control of the CAVs set-point on positions and speed (more details can be found in [5] and [6]).

Conclusions

To summarize, the achievements in FY 2018 are:

- C. We have developed a reinforcement learning algorithm to minimize energy consumption from signalized intersections leveraging data availability in a CV environment, a multi-reward learning approach to account for the trade-off between mobility and energy performances at signalized intersections. With the balanced reward function accounting for energy and mobility, it is possible to achieve desired traffic state with minimal energy and maximized mobility.
 - iii. The algorithm is tested in a simulation environment with calibrated real-world signalized intersections to assess the mobility and energy impacts
 - iv. The data-rich CV environment provides the suitable platform to implement learning-based algorithms that would be well suited for a stochastic traffic environment. The ability to learn from transitions in traffic states makes RL-based control more flexible and efficient compared to existing fixed, semi-adaptive, and actuated control schemes.
- D. We developed the data-driven and dynamic recursive input/output traffic queue model to calculate real-time traffic queue specifically during red, green, and yellow signal periods. In this model, we make use of traffic signal timings and data from pair of loop-detectors such as number of vehicles entering and leaving the corridor along with their speeds.
 - v. We also designed the proportional controller along with actuator and saturation to control the input-output model such that the traffic queue vector can be maintained at an appropriate reference queue.
 - vi. Further we developed the stochastic control algorithms to control static and linear dynamic versions of stochastic distribution traffic queue model such that the probability density function is as narrow and as left as possible. Our MATLAB simulation results confirm this convergence of actual probability density function using control algorithms.

Key Publications

1. SMA B. Al Islam, H. M. A. Aziz, H. Wang, and S. Young, "Minimizing energy consumption from connected signalized intersections by reinforcement learning" Accepted in IEEE ITSC 2018 conference, Maui, Hi, November 4-7, 2018.
2. SMA B. Al Islam, Ali Hajbabaie, H. M. A. Aziz. A Real-time Network-level Traffic Signal Control Methodology With Partial Vehicle Information. Accepted for presentation in the 2019 Transportation Research Board Annual Meeting. Paper no. 19-02829
3. Wang, Hong, H. M. Aziz, Stanley E. Young, and Sagar Patil. "Control of networked traffic flow distribution: a stochastic distribution system perspective." In Proceedings of the 1st International Conference on Internet of Things and Machine Learning, p. 37. ACM, 2017.
4. Wang, Hong, H. M. Aziz, Stanley E. Young, and Sagar Patil, Optimal operational control for signalized intersections for smooth traffic flow with minimized energy consumption, podium at ASCE

International Conference on Transportation and Development, Podium Presentation, Pittsburgh, July 2018.

5. Wang, Hong., H. M. A. Aziz and S. Young, Non-Signalized Intersections Control – a Collaborative Fault Tolerant Control Perspective, ASCE International Conference on Transportation and Development, Podium Presentation, Pittsburgh, July 2018.
6. Wang, Hong., Keynote presentation, Collaborative fault tolerant control for complex systems, IFAC Safe process August, 2018, Poland, 2018 (this is the largest conference on fault diagnosis and tolerant control organized by International Federation on Automatic Control taking place once every three years)

Acknowledgements

We acknowledge the contribution from team members including: SMA Bin Al Islam from Washington State University, Sagar Patil from Pacific Northwest National Laboratory, Stanley E. Young from National Renewable Energy Laboratory.

VI High Performance Computing and Big Data

VI.1 Reinforcement Learning-based Traffic Control to Optimize Energy Usage and Throughput (ORNL)

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Project Funding (FY18): \$310,000	DOE share: \$250,000	Non-DOE share: \$60,000

Project Introduction

The US roadways are critical to meeting the mobility and economic needs of the nation. The United States uses 28% of its energy in moving goods and people, with approximately 60% of that used by cars, light trucks, and motorcycles. Thus, improved transportation efficiency is vital to America's economic progress. The increasing congestion and energy resource requirements of transportation systems for metropolitan areas require research in methods to improve and optimize control methods. Coordinating and optimizing traffic in urban areas might introduce hundreds of thousands of vehicles and traffic management systems, which can require high-performance computing (HPC) resources to model and manage. In this work, we seek to use machine learning, computer vision, and HPC to improve the energy efficiency aspects of traffic control by leveraging GRIDS MART traffic cameras as sensors for adaptive traffic control, with a sensitivity to the fuel consumption characteristics of the traffic in the camera's visual field. Traffic control use cases using reinforcement learning have been published and achieved good results. Surveys from DOE national laboratories estimate that the fuel cost of idling is six billion gallons wasted annually [1]. GRIDS MART cameras—an existing, fielded commercial product—sense the presence of vehicles at intersections and replace more conventional sensors (such as inductive loops) to issue calls to traffic control. These cameras, which have horizon-to-horizon view, offer the potential for an improved view of the traffic environment, which can be used to generate better control algorithms.

Objectives

There are two primary objectives in this project. The first is to develop algorithms that essentially teach GRIDS MART cameras to estimate fuel consumption of vehicles in their visual field. The second is to use this capability to improve energy efficiency by changing timing and phasing of traffic lights, while minimizing penalties to throughput and mobility. HPC can play a role in both objectives by allowing more complete exploration of the machine learning architectures, parameters, and methods that enable the capability to determine vehicle types. HPC-based simulations that model traffic and capture the performance of GRIDS MART cameras in estimating the visual field (extrapolated from real data using developed algorithms and models) serve as training and testing data for reinforcement learning algorithms that learn policies for traffic camera control. The key outcome of this work will be control strategies generated through a novel reinforcement learning framework, with performance measured through simulations and validation data and oriented toward the GRIDS MART sensing capability. Other important outcomes include projections of the required sensing capabilities to achieve these control strategies. This will pave the way for future research to expand the number of studied intersections, investigate the potential of wide-range coordinated control, add

naturalistic driving study data for higher resolution and simulation detail, extend sensing capabilities to other technologies such as RFID/cellular and/or connected vehicle technology, and incorporate direct vehicle emissions sensing to minimize cumulative emissions measured.

Approach

The GRIDSMART cameras will be trained to estimate fuel consumption by using a ground-based camera system located under a GRIDSMART instrumented intersection. ORNL has three GRIDSMART cameras on site, and these will be used to collect data. The simultaneous capture of the ground-based camera image with the GRIDSMART camera image will allow a view from the “GRIDSMART perspective” along with a view from the ground camera. The latter will then be classified into a vehicle class (i.e., make and model), ideally using a commercial application procured for this purpose. ORNL will leverage an existing, ongoing project that is collecting data on the reservation as part of another project. The data used here will allow the creation of a training set of images—from the unique GRIDSMART view—that will be used to create a machine-learning model to classify vehicle make and model and therefore estimate fuel consumption. There are contingencies built into this process. First, there could be better methods to estimate the fuel consumption that simply estimating the make and model, and these approaches will be explored. Second, if sufficient data is not collected, an estimate will be made using ground data from existing data sets [2]. Finally, we will also attempt to leverage coarse statistics such as vehicle size to determine whether there can be a reasonable substitute for true vehicle classification. The approach is shown in Figure VI.1.1.

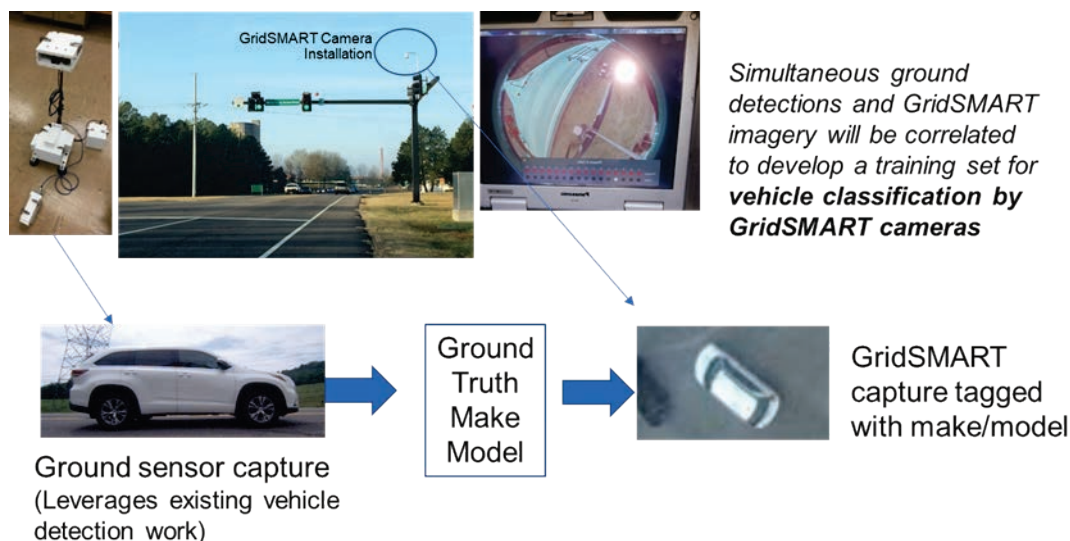


Figure VI.1.1 Data collection to estimate fuel consumption using GRIDSMART cameras. GRIDSMART installations at ORNL will be used in conjunction with a ground imaging system under development for another project. The simultaneous captures will be used to produce a library of images suitable for training a machine learning algorithm to estimate fuel consumption.

The GRIDSMART cameras will be trained to control timing and phasing for improved fuel efficiency by reinforcement learning and simulations (on HPC). The HPC simulations will create derived training, validation, and testing data to explore control strategies based on reinforcement learning (RL) with automated vehicle identification algorithms at varying resolution using the Participant video data. The control strategies development will start with single intersections and expand to multiple intersections with studies on scalability and impact. The HPC simulations will be performed on HPC, but with a goal of producing control strategies that can be deployed in environments with a small computational footprint such as a distributed network of GRIDSMART cameras. RL finds solutions to problems where an actor or set of actors learn to respond to dynamic environmental conditions to achieve an overall optimized solution such as winning a game or

controlling a process. In this collaboration, the actions are the activation of one or more traffic signals in response to sensed vehicle types (and corresponding fuel economy metrics), vehicle dynamics, and throughput objectives. The optimization goal is a combination of throughput and energy efficiency. The huge input space (combinations of vehicle types, vehicular dynamics, and multiple signal lights) represents a large dimensional problem that will require HPC for simulations and deep RL for solutions. Our initial planned approach is to develop a custom simulation environment for the vehicle simulation, given the scope of the proposed work, as a simple proof of concept.

Results

We created algorithms and a process to capture simultaneous GRIDSMART images and ground imager system images, align them, and label them. GRIDSMART data at the ORNL locations must be captured using a USB hard drive plugged into the controller. GRIDSMART personnel helped ORNL confirm the method for this capture and also helped ensure the controllers were time synchronized, which was critical to use timing data to correlate the ground imager captures with the GRIDSMART data. Computer vision algorithms were developed to segment the vehicles from the background using a process similar to GRIDSMART's implementation. In Figure VI.1.2 a simultaneous capture with the GRIDSMART imager and the ground truth imager is shown. The commercial application labeled this ground capture as a “Ford Transit Connect,” which is inserted into the image for illustration in the upper left corner. Multiple images such as these have been collected and will continue to be collected into 2019. As of the end of September 2018, approximately 12,600 vehicles have been collected. We note that a percentage of these have ground truth labels spanning 474 classifications. Although this is substantial, more data is needed to create deep learning models for effective classification, so continuous collections are ongoing to expand the set.

Given that more data is needed to effectively create a model for vehicle classification from the GRIDSMART view, we used two contingencies to estimate vehicle classification performance for our simulations. First, we used a table of vehicle types and the length and width estimates of the vehicles to try and estimate vehicle fuel efficiency using a linear regression model. Second, we used an open-source database of vehicle images to estimate classification performance and its impact on fuel efficiency estimation. (Note that for our initial analysis we did not include large commercial trucks, which will have a definite impact on the system performance when we are able to include them.) The estimated fuel economy with this model and perfect measurements is RMS error of 2.85 MPG, but conversations with GRIDSMART indicated that there can be substantial error in such a measurement from any computer vision platform. We found that the regression model rapidly degrades with small measurement error; even a 500 mm mean error creates an RMS error of approximately 5.8 MPG. Therefore, we believe the utility of a measurement-based system will largely be found in discriminating commercial trucks (particularly “18 wheelers”) from passenger vehicles.

Our second effort used the dataset from [2]. Although this was taken from the “ground view,” we believe it serves as a good estimate for what might be possible with a full data set from the GRIDSMART vantage. We retrained a convolutional neural network based on the Alexnet topology [3] to act as a vehicle make/model classifier. This was inspired by the example of [2], which served as a good baseline for the exercise. We trained using 70% training data, 15% validation data, and 15% testing data and evaluated our performance on the test data set aside. We also degraded the image resolution to simulate actual degradation of the image quality from the GRIDSMART imager at ORNL, at ranges of 0 m, 20 m, 40 m, and 60 m. Finally, we used the classifier to estimate fuel efficiency visually by assuming if we successfully identified the make and model of the vehicle, our error was 0 MPG; otherwise, we used the erroneous classification as the MPG and measured the RMS error between this estimate and the actual value. The results are summarized in Table VI.1.1. An example of a tracked vehicle from 60 m to the stop light is shown in Figure VI.1.3.

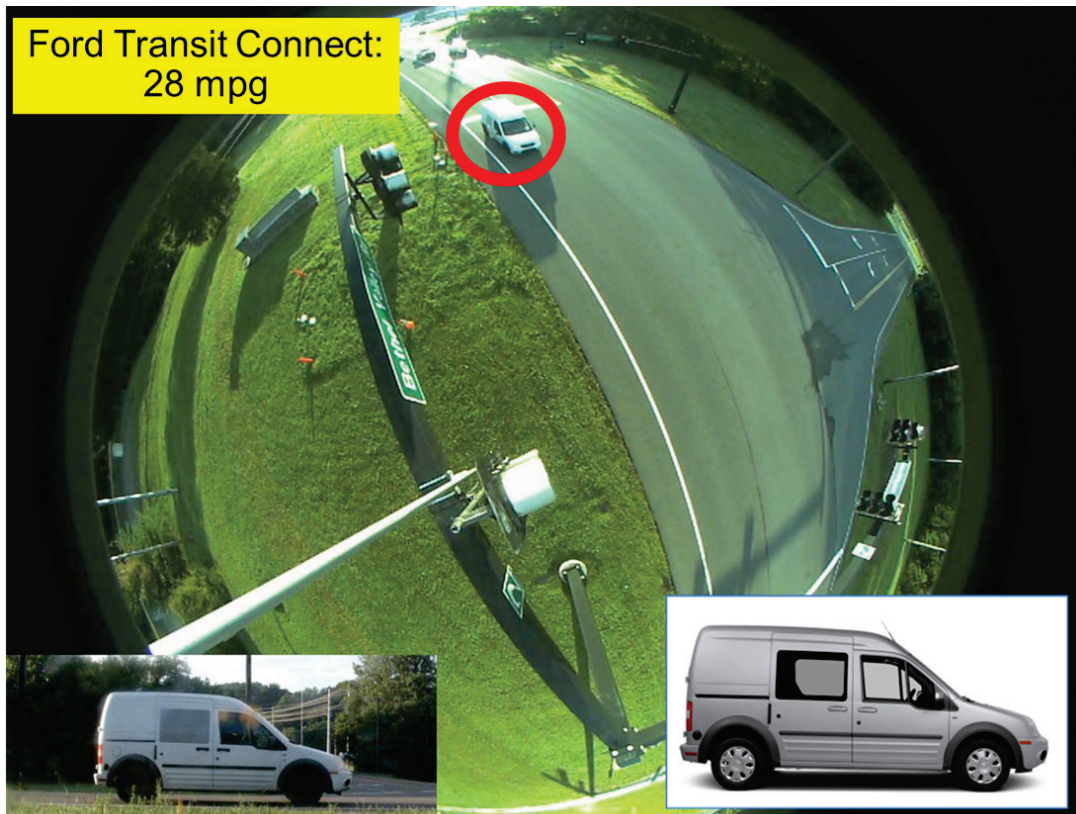


Figure VI.1.2 GRIDSMArt capture (overview) with simultaneous ground imager collection (bottom left). The commercial application labeled the ground imager data as a “Ford Transit Connect,” which has an estimated fuel efficiency of 28 MPG. The bottom right depicts an image of the same vehicle, found independently, confirming this labeling. Using this and many more captures we can begin to teach the GRIDSMArt cameras how to estimate vehicle fuel consumption.

Table VI.1.1 Estimates of Fuel Economy using CNN Baseline Model

Range to Vehicle (m)	Classifier Accuracy (%)	RMS MPG Error
0	33	3.5
20	16	5.1
40	3	6.7
60	1	10.0



Figure VI.1.3 Example of an actual tracked vehicle from the ORNL GRIDSMART camera. The image degradation due to resolution and the fish-eye lens is profound at longer distances and degrades classifier performance, as shown in Table I.1.1.

Given the error based on the make and model, we are interested in determining whether there are better methods for vehicle classification that can be more robust to RMS estimates. These include estimating the length and width with convolutional neural networks (CNNs) and developing a topology that focuses on improving the overall MPG estimates. At the end of September 2018 we used the MENNDL processing engine [4] on ORNL's Titan supercomputer to attempt to evolve a better topology for fuel efficiency estimates. Those initial results were indeterminate, but we plan to continue this effort in FY 2019, leading to a role for HPC in the actual first objective for the project.

Conclusions

In this period of performance, we have identified data sources at ORNL and successfully collected camera images with the assistance of GRIDSMART. The data has been correlated with ground-level collections, and we have used a commercial application to classify the vehicles, allowing us to begin building a data set for our first objective. We have developed and deployed computer vision algorithms to segment vehicles from the background, which allows us to capture a view of the identified vehicle type from multiple ranges from the camera. Vehicle collections are ongoing and are expected to continue through the duration of the work with weekly data pulls. Given the limited scope of the project, we took the approach of having contingencies for our estimation method. Estimates based on vehicle size for passenger vehicles can produce a good estimate of fuel consumption characteristics, with RMS error under 3 MPG, but these estimates are susceptible to error. We believe relying on vehicle size estimates will still be beneficial when we consider commercial vehicles, which are typically larger and much less fuel efficient. We have also elected to project an estimate of classification performance using an open-source data set, with an estimated RMS error in fuel consumption of 3.5 MPG for noncommercial, passenger vehicles at close range with degradation as the range increases. We used the MENNDL HPC algorithms to attempt to improve the CNNs that estimate fuel consumption, with limited

success in this performance period but with more work to be attempted in FY 2019. Finally, our simulation efforts will be our primary focus in FY 2019, with three potential approaches: a cell transmission model, an open-source traffic simulator, and a simplified custom simulator.

Key Publications

None to date.

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Acknowledgements

We acknowledge the contributions of the ORNL team, including Matt Eicholtz, Russ Henderson, Johnathan Sewell, Eva Freer, Regina Ferrell, Travis Johnston, Sean Oesch, Thomas Naughton, Wael Elwasif, Steven Young, and Derek Rose.

VI.2 High Performance Computing for Mobility (HPC4Mobility) (LBNL)

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Start Date: October 1, 2017

End Date: September 30, 2019

Project Funding (FY 18): \$250,000

DOE share: \$250,000

Non-DOE share: \$0

Project Introduction

Traffic planners often use some instantiation of a static traffic assignment problem to estimate traffic states in their cities. To accommodate changes in the demand profile over an entire day, the problem might be broken up into time slots of interest and static traffic assignment solutions are run for each slot. Example time slots are early morning, morning rush hour, mid-day, evening rush hour, late evening. Because of the complexity of the network and the scale of the demand, these models often take many hours or perhaps even days to run.

The purpose of this project is twofold: 1) leverage High Performance Computing capabilities to reduce the computing time associated with running these models on urban scale problems, and 2) examine the energy impact of urban-scale traffic by developing and implementing a scalable assignment model that optimizes for fuel consumption. The energy optimization function can then be compared to the typical travel time optimization that is traditionally used in traffic assignment models to determine real-world impact of considering fuel consumption in system level traffic control. The City of Los Angeles, CalTrans and the UCB Connected Corridor Program are providing the modeling expertise and feedback for this effort. HERE Technologies is providing urban-scale GPS device data to inform our modeling approach.

This work will contribute to LBNL's efforts to develop new processes, analytical tools, program designs, and business models to advance the state of the art in next-generation sustainable transportation solutions.

Objectives

The work proposed for this project will provide a simple but ambitious proof of concept that traffic assignment and optimization models can be efficiently implemented on HPC platforms. The goal of the project is to provide a computational framework capable of ingesting urban-scale demand data and produce an optimized network loading estimate from the data. The models will include traditional static user equilibrium, as well as a dynamic traffic assignment model capable of handling time varying components, e.g. network variations through the day, special events and other dynamic phenomena. The project will follow the steps outlined below.

1. Formulation of a **processing pipeline** to handle map data and demand data in an HPC setting. This involves creating a common mechanism for ingesting map data at scale on distributed platforms and implementing distributed models with varying demand data profiles. At the end of the work, the success

of this step can be demonstrated by swapping two different models and two different demand data types at very little set up cost and running both at urban scale.

2. Implementation of at least **two models at urban scale**, one static (i.e. user equilibrium or game theoretic extension), and one dynamic (i.e. dynamic traffic assignment capable of handling network state aware routing). These two models will be demonstrated at scale on the entire LA Basin or a similar large-scale network.
3. Derivation of an improved **energy optimization** function, that can be mathematically proven to converge with a unique solution, will be posed and integrated into the optimization code for travel assignment.
4. **Benchmark data scenarios.** The effort will be showcased by demonstrating HPC computing capabilities on a suite of demand data (provided to us by SCAG and in collaboration with LA Metro). With these different demand data files (for example corresponding to nominal days, weekends, special events, perturbations such as weather, fires etc.), the HPC platform will be used to demonstrate our computational abilities in scenarios conceived and reviewed with LA Metro.

Approach

The approach was to begin with a traditional static traffic assignment model in which the routing for all origin and destinations are computed in parallel on high performance computing facilities. Convergence of the numerical methods rely on the solution of convex programs, or extensions of these. This step demonstrates the ability to parallelize the Frank Wolfe algorithm. Implementation of the traffic assignment problem on a large-scale network follows this initial demonstration. Introduction of a fuel optimization focus is then integrated into the implementation by modifying the optimization function to include data-driven models from real-world chassis dynamometer test data. The final step will be to address the dynamic traffic assignment problem through iterative static traffic assignment solutions with high performance simulation capabilities.



Figure VI.2.1 LA Basin road link/intersection network

A small and well researched part of the LA Basin, known as the Connected Corridor, that provides detailed demand data was selected as the initial demonstration area for a distributed traffic assignment solution. The road link/intersection network for this area of interest is shown on the left. A Frank Wolfe algorithm is used for implementing this particular traffic assignment problem when optimizing travel time. This code was further developed to include the energy optimization case. The proposed energy model is a combination of the CMEM fuel consumption model [1], with a traditional BPR function. To ensure convergence, the speed – fuel consumption curve was slightly adjusted to make the curve convex which allows the gradient descent method to converge.

This geospatial area represents 28,000 road links. A demand model of 100,000 Origin/Destination pairs from the SCAG demand profile are applied to this road network. Note that a static assignment does not deal with the dynamic behavior that results from network dynamics, it simply assigns an O/D routing solution that minimizes travel time for all mobile entities so that no driver can unilaterally reduce his/her travel costs by shifting to another route. This is often referred to as the Nash Equilibrium.

To extend our optimization focus further, we also included a notion of system optimization in context of these two different objectives. Consequently, four key cases are the subject of the investigation:

1. Energy optimized at the system level
2. Energy optimized selfishly at the vehicle level

3. Travel time optimized at the system level
4. Travel time optimized selfishly at the vehicle level.

With these four cases implemented on a small-scale network the next step it to address larger scale road networks and dynamic assignment models.

In order to focus on pragmatic results that can impact city level government, existing infrastructure from another VTO supported program - Big Data Solutions for Mobility Planning – was leveraged and extended for this program. An urban scale simulation program that has been implemented on HPC, called Mobiliti, had previously built an infrastructure for ingesting large-scale demand models and urban-scale road networks. As a part of the Mobiliti simulation work an efficient network routing algorithm was also implemented. This ingestion infrastructure and the routing algorithms were integrated into a Frank Wolfe solution. The Mobiliti routing solution optimizes the compute time and is capable of identifying optimal routes through the network instead of approximate solutions, which are often used to reduce computational loads. With this infrastructure, a processing pipeline is in place for this project that provides ingestion of urban-scale demand profiles and networks and high-speed routing capabilities.

Instead of optimizing the system based on the travel time, we extended existing algorithms for the traffic assignment problem (TAP) with new objective functions to incorporate vehicle fuel consumption. Specifically, we use a vehicle fuel consumption curve, i.e. fuel consumption rate vs. speed curve from the developed aforementioned data-driven CMEM [1] energy models. We conducted multiple experiments to investigate the patterns of the four different traffic assignment methods, i.e. time-based user-equilibrium (UET), time-based system-optimal (SET), fuel-based user-equilibrium (UEF) and fuel-based system-optimal (SEF). Preliminary visualization programs were developed to perform exploratory analysis on these four different cases. The procedures to solve this problem on the supercomputer Cori is as follows:

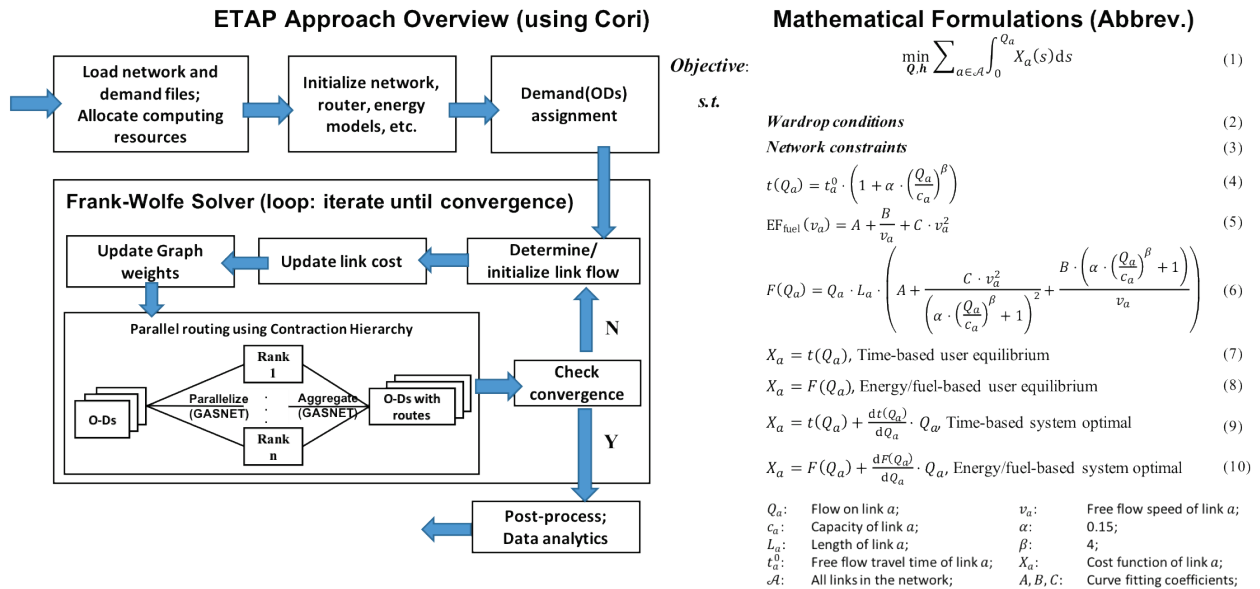


Figure VI.2.2 ETAP Approach Overview and Mathematical Formulas

Results

The figures below show the results of these optimizations. Links that represent the top 1000 flow values are shown with blue at the lower values and green/red as the higher values. Each optimization focus shows a variation in flow as a result of the optimization.

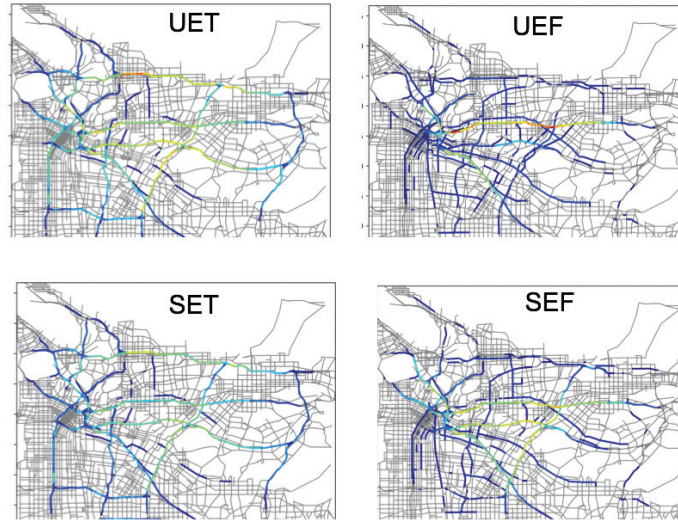


Figure VI.2.3 Flow Impact Due to Different Optimization Solutions

Typically, cities are interested in optimizing travel time. Realizing that travel time optimizing is usually accomplished by selfish routing – e.g. a traveler will pick the travel time that is shortest for their own goal – we provide a view that is normalized to this particular perspective. The figures below show how travelers are impacted for each specific case in terms of distance traveled and travel time.

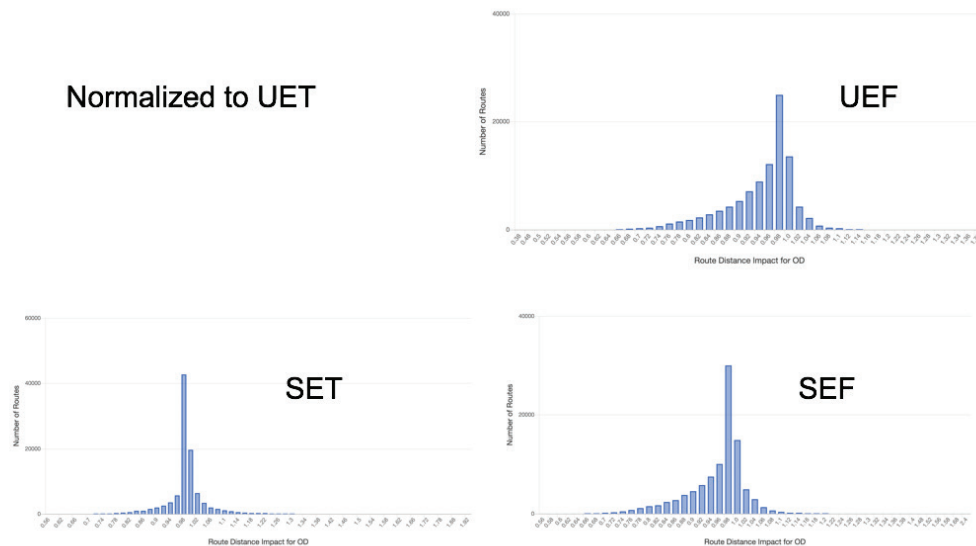


Figure VI.2.4 Distance Impact on Travelers Due to Different Optimization Solutions: Normalized to User Equilibrium Travel Time

The peaks in Figure VI.2.4 represent travelers that experience no impact in these scenarios. The tails of the graphs show the percentage distance impact from their path if this were optimized for travel time only.

Total vehicle miles traveled for each case is shown below with User Equilibrium that is optimized for fuel consumption results in the lowest vehicles miles traveled.

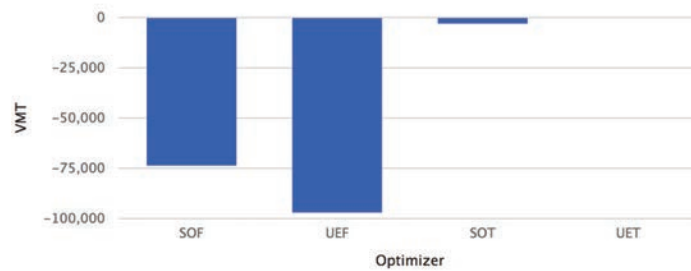


Figure VI.2.5 Difference in Vehicle Miles Traveled with respect to User Equilibrium Travel Time Optimization

In addition to distance, travel time impacts were also determined and are shown in the figures below. As expected, travel time suffers if alternate optimization solutions are considered.

Similar to the distance impacts, the peaks in Figure VI.2.6 represent travelers that experience no impact in these scenarios. The tails of the graphs show the percentage travel time impact from their path if this were optimized for travel time only. Clear from this analysis is the complexity of the tradeoffs in transportation system optimization solutions.

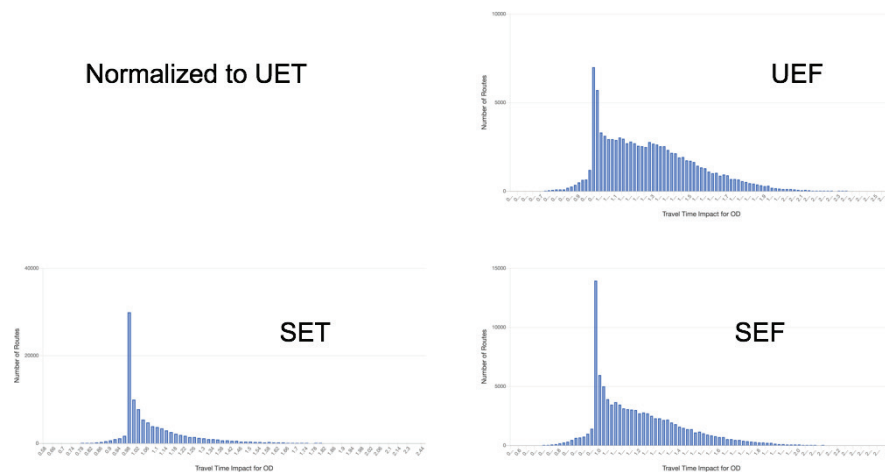


Figure VI.2.6 Travel Time Impact with Respect to User Equilibrium Travel Time Optimization

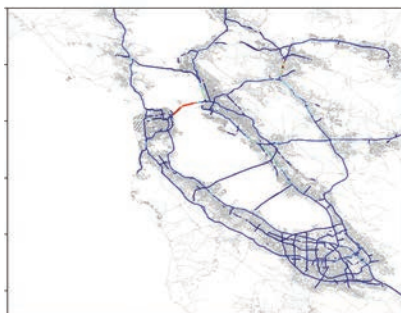


Figure VI.2.7 Bay Area Network with highlighted highest flow links for UET solution

Our next step was to extend this model to address a much larger, urban-scale model. A network and demand model that provides a foundation for research work at VTTI {ref} is being integrated into the infrastructure. This model is based on the HERE Technologies map that is a high-quality representation of the Los Angeles network. As this is being implemented, an alternate urban-scale network for the Bay Area was investigated.

The Bay Area network has 2 million road links and the traffic demand includes 22 million origin-destination pairs. The preliminary performance results of a total solving time of 45 mins, was implemented on the LBNL Cori supercomputer with a single computing node and 64 threads. Figure VI.2.7 indicates the highest flow links for a UET solution. An important note is that the compute time for this solution is significantly lower than any traffic assignment solutions at this scale. In

fact, due to the computational loads current solutions break the problems into smaller time scale solutions and still might, in the best case, run in a compute time on the order of many hours. The figure at the left shows top 5000 Flow Links in a UET optimization scenario.

To initiate a discussion of metrics associated with control of an urban-scale fleet, we also show the network usage for our four optimization cases. We wish to explore how optimization drives network use. This is important if we wish to consider how to best use our available network resources. Note that the larger scale urban network of the Bay Area that contains bridges and reduces the connectivity among regions significantly changes the direction of impact on VMT. Once again demonstrating the complexity of tradeoffs in transportation system planning and optimization.

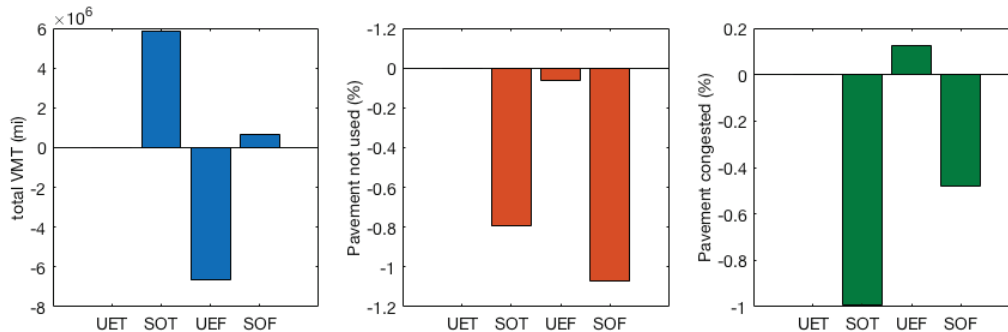


Figure VI.2.8 Metrics to Consider for Urban-Scale Fleet Level Optimization

Conclusions

The complexity of road network connectivity and demand modeling dynamics has long been the challenge for urban planners and urban modeling and simulation research. From a practical standpoint, first order estimates are currently being used to predict the energy impacts of emerging mobility solutions. For example, the impact of CAVs on VMT and energy footprint have been estimated based on census data and statistics of travel behavior. HPC, data science and advanced modeling, will allow DOE to develop the ability to perform more realistic and detailed computations. Such capabilities are essential, as the complexity of the transportation infrastructure cannot be aggregated and comprehensively modeled mathematically. As such local/regional, State, and Federal level will need to rely on models that can be considered at a granular level, yet still at scale. This initial work has shown the complexity of the tradeoffs associated with optimizing traffic assignment. With HPC, we are able to investigate scaled optimization scenarios with a compute time on the order of less than an hour of which will enable cities to reimagine their opportunities to offer their citizens and businesses better environments in which to live.

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VI.3 Big Data Solutions for Mobility (LBL, ANL, PNL, ORNL)

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Start Date: December 15, 2017 End Date: December 31, 2020
Project Funding (FY18): \$4,000,000 DOE share: \$4,000,000 Non-DOE share: \$0

Project Introduction

The purpose of this program is to develop the data science and HPC supported computational framework needed to build next-generation transportation/mobility system models and operational analytics. In order to represent real-world urban systems, the models and analytics must scale both in spatial and temporal complexity. We will build on previous work in transportation systems, electrical grid analytics, and atmospheric modeling that has been developed within the partnered laboratories.

This work will focus on four key objectives that underlie critical transportation modeling challenges:

- Develop transportation system modeling approaches that permit parallel implementation or are limited by computational complexity and can be implemented on HPC,
- Develop methods for capturing and adjusting for data velocity and veracity across both temporal and geospatial scales,
- Understand the appropriate role of machine learning, agent-based models, and streaming analytics including feedback mechanisms, extensibility, and propagation of data veracity through those systems, and
- Develop mechanisms for semantically tuning lower level learning systems in order to create robust automated solutions.

HERE Technologies is providing urban-scale GPS device data to inform our modeling approach.

Objectives

By leveraging high-performance computing and big data analytics we will further our understanding of transportation systems. Specifically, current transportation planners in urban areas do not have adequate tools for understanding the complex dynamics of their cities. Our objective is to focus on creating an ability to rapidly model urban scale transportation networks using real-world, near real-time data to optimize traffic for mobility, energy and productivity. Specific goals include:

- Learn patterns in the real-world data to inform our modeling with the goal of understanding how to respond to transient events such as accidents, emergency response and transportation network changes
- Investigate the drivers of those patterns and how we might impact those patterns and optimize on energy versus traditional throughput models
- Develop control ideas for large-scale urban transportation networks through tractable computational simulations that can describe emergent behavior of vehicle dynamics
- Provide urban scale modeling tools that can integrate into urban planning and design processes and tools.

Approach

Project Tasks

1. Define Appropriate Role of HPC in Transportation Planning
 - Determining the best use of HPC capabilities in the Transportation Planning field. Initial focus was on establishing HPC projects at three labs. Follow on focus is to establish relationships with Cities to confirm that the activities of the project will be valued by actual planning operations.
2. Automated Collection, Modeling and Validation of Data Using HPC
 - This task focuses on the real-world data. The data will eventually come from the Connected Corridor program supported by CalTrans in Los Angeles. Initial focus was to catalog available data, establish NDAs for data access, and send sample data sets to researchers.
 - Follow on focus:
 - Machine Learning of Geospatial Temporal Data
 - Probe Data Veracity
 - Data Fusing and Modeling
 - Semantic Modeling
 - Demand Modeling
 - Model Validation
3. Develop HPC Network Models
 - This task focuses on the modeling of urban scale transportation networks. Initial focus was to stand up some agent-based models to investigate emergent behavior and traditional traffic assignment at scale. The goal of this work is to build models that can scale to a full urban environment. This means realistic vehicle volumes (e.g. 7-8 M vehicles for the Bay Area) and a full-scale link/node network (e.g. 2 M links and 1.1 M nodes). Our objective is to use HPC to run these simulations in a significantly shorter time than current tools. Our second objective is to compare modeling

approaches. For example, compare and cross-validate traffic assignment models, agent-based models and microsimulation models. Our third objective is to seek out reasonable travel demand models that have been validated by city governments as input to these models. Once our models are validated, our final objective is to evaluate the possibility of running our models on HPC and generating enough data to then apply machine learning to the output of the models. The successful completion of this step would then allow for city models to be shared that may not need HPC to run in a reasonable time.

Follow on focus:

- Traffic Assignment with Energy Optimization
- Parallel Discrete Event Simulation
- Machine Learning of City Models
- Model Validation

1. Couple Data Ingestion into Modeling Platform

Define a common platform for the data ingestion and modeling tools. This includes data ingestion and preprocessing methods for raw data cleaning, error detection and correction, and missing data imputation

Table VI.3.1 details the responsibilities and the staffing for each task. The machine learning (ML) activities for geospatial temporal data and energy modeling are collaborative efforts between ANL and LBNL.

Table VI.3.1 Core Tasks and Associated Lab Team Responsibilities

	LBL	ANL	PNNL
Task 1: Define Appropriate Role of HPC in Transportation Planning	<ul style="list-style-type: none"> • Identify key HPC Technology Gaps <i>Jane Macfarlane</i>		
Task 2: Automated Collection, Modeling and Validation of Data Using HPC	<ul style="list-style-type: none"> • Define and Access CC data • Define Data Veracity Analytics • Model Validation • ML of Geospatial Data • Semantic Modeling <i>Jane Macfarlane; Marta Gonzalez; Brian Gerke; Ling Jin; Tom Wenzel; Summer Intern; GSRs</i>	<ul style="list-style-type: none"> • Evaluate DCRNN/LSTM for ML of Geospatial Data • Semantic Modeling <i>Prasanna Balaprakash; Eric Rask; GSRs</i>	<ul style="list-style-type: none"> • Streaming Data Analytics <i>John Feo; Arif Khan; Vinay Amatya</i>
Task 3: Develop HPC Network Models	<ul style="list-style-type: none"> • Parallel Discrete Event Simulation • Extended TAP • Energy Model* • ML of City Models 	<ul style="list-style-type: none"> • ML of City Models* • Energy Model* <i>Prasanna Balaprakash; Eric Rask; GSRs</i>	

	Alex Bayen; Jane Macfarlane; Cy Chan; John Bachan; Bin Wang; GSRs		
Task 4: Couple Data Ingestion into Modeling Platform	TBD	TBD	TBD

* Indicates new responsibilities – Energy Modeling has shifted to LBNL and ANL, and ML of City Models is a new task that we hope to consider as work efforts in PDES and ML of GeoData matures.

Results

Our initial activities focused on standing up the modeling efforts. Argonne National Lab took on the initial data modeling efforts focused on the geospatial data - specifically the inductive loop sensors that are installed in the Connected Corridor region. The objective of this work was to use automated machine learning on ANL HPC computing facilities to develop predictive models of speed and volume at the locations of the loops. Lawrence Berkeley National Lab took on the development of a parallel discrete event simulation and non-real-time data veracity filters. Pacific Northwest National Laboratory took on the development of real-time data ingestion tools using their HPC capabilities. ORNL began evaluating energy modeling. Key accomplishments include:

Data Analytics

(ANL): Established automated machine learning that optimally designs Long Short Term Memory neural nets with loop detector data. For a preliminary proof-of-concept application, a stacked LSTM was applied to limited (2018-only) single-detector data and used to make predictions at 15/30/60 min ahead. Preliminary results were promising for both flow and speed predictions.

Temporal Convolution neural networks were also considered and showed even better results with a simpler process. Temporal Convolutional Network (TCN) architecture elements are displayed below to provide an overview of the methodology [11].

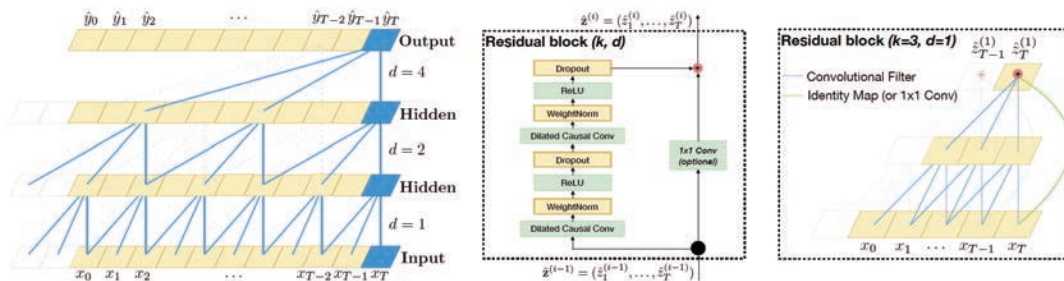


Figure VI.3.1 TCN Architectural Elements

A network that integrates data from 85 geospatially distributed inductive loops was created. This integration converged to a hyper parameter selection much quicker due to their geospatial dependencies. The MAE was improved with the TCN architecture and resulted in a predictive speed MAE of less than 3.5 kph and flow MAE of less than 35 vehicles per hour with a prediction horizon of 60 minutes. This is a 12% improvement for speed and ~20% for flow prediction improvement over an LSTM approach. We believe the TCN approach is the appropriate architecture for dealing with geospatially distributed temporal data. The next step will be to determine if this will be an appropriate mechanism for learning from GPC probe data and whether there is an opportunity to fuse both data sources into the architecture.

(LBNL): Established a team to develop data veracity analytics and associated remediation of incomplete or incorrect data. A software package for processing GPS data is being developed to identify and flag potentially

erroneous data. Our intent will be to open-source this package to the mobility data analytics community. The following taxonomy of potential data inconsistencies has been identified:

- Duplicate timestamps: two or more points in the same trajectory having different positions but identical timestamps.
- Failure to update position: latitude and longitude data are exactly the same from one timestamp to the next.
- Probe confusion: trajectories for multiple different devices (probes) are mapped to a single device ID.
- Spatial outliers: a single point lies far from the route being followed by the trajectory both prior and subsequent to the point.
- Sudden changes in sampling rate: a trajectory's timestamps have been increasing at a regular frequency, which is suddenly interrupted by a point having a different timestamp increment, often accompanied by an unrealistic velocity.
- Unrealistic velocities not otherwise categorized: these are candidates for additional scrutiny and classification.

(PNNL): Developed a code base to analyze an example transportation corridor - AMS Dallas Testbed Analysis that includes

- Temporal data such as the average traffic per hour aligned with weather data.
- Spatial information such as the approximate latitude-longitude of the closest point on the road.
- Removal of spurious outliers of traffic volume and speed based on a learned density estimation.

A prototype code base was developed using Open Street Map API and Road Network Analysis Tool OSMNx, in order to validate traffic information and generate meta information using two traffic datasets: i) Publicly available Wyoming CV Pilot Basic Safety Messages (BSM) and ii) Portland GPS Fleet Data. The Wyoming BSM dataset covers 402 miles of I-80 corridor in Wyoming. Each participating vehicle sends information about its speed, acceleration, etc. (total 69 features) and there are roughly 3.1 million such records each day.

Additionally, a Portland GPS fleet data that contains GPS location, speed, acceleration, etc., every 10-15 seconds is being evaluated. There are about 5,000 records per day. The prototype code currently checks validity of the data, for example, given two timestamps and distance traveled, it computes average speed and compares with the reported speed. The software also generates meta information, for example, given a location, it obtains the posted speed limit through Open Street Map API and compares with the reported speed in order to identify congestion. Augmenting the traffic data with weather information (NOAA) and accident information (DOT) is underway.

Urban Dynamics Modeling

(LBNL): An existing simulation designed explicitly to leverage HPC capabilities and previously used for grid simulation, was repurposed to model a transportation network. This new system, named Mobiliti, currently models the Bay Area as an initial test case. A readily available Bay Area network extracted from Open Street Map and transformed to a unidirectional link representation provides the model for the road network. After initial evaluation of several vehicle routing algorithms (e.g. Dijkstra's algorithm and A*), a contraction hierarchies algorithm was selected. As a result of this update, the routing is much faster, and it is capable of identifying optimal routes through the network instead of approximate routes. This highly efficient routing algorithm enables us to study the impact of dynamic re-routing.

After a coordination discussion with local transportation officials from San Francisco and San Jose, a validated demand model consisting of 27.6M trip legs, representing the traffic demand from 7.3M residents was

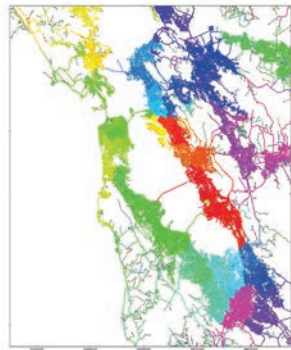


Figure VI.3.2 Bay Area Road Network simulation

obtained from SFCTA. Of these original trip legs, 21.7M result in vehicle trips through the road network, while the remaining are satisfied through walking or cycling. Since the SFCTA model works with demand at a granularity of traffic analysis zones (TAZ), we adapted the model to generate node-level inputs for Mobiliti via random node selection within the origin and destination TAZs. Since demand may not be uniformly distributed among each TAZ, we are identifying ways to modify the resulting demand to further increase the fidelity of our simulation. We have additionally optimized the parallel decomposition network partitioning strategy for the SFCTA demand model. Excluding initialization time, we can simulate 21M trip legs during one simulated day in less than 30 seconds using 32 nodes (1,024 compute cores) of the Cori supercomputer. Intelligent geospatial partitioning of the dynamics shown in the figure on the left is key to the power of this modeling methodology as it uses the message passing power of high performance computing.

Energy Modeling

(ORNL): A modal-based approach for estimating energy consumption of EVs was investigated that allows the energy estimation. Autonomie is used to generate ground-truth energy consumption, and three preliminary steps are used to develop the modal-based approach for EV fleets. Sample EV models were established and the energy use of selected vehicles was generated by simulating a wide range of operating conditions. Classification and regression tree (CART) methods were applied to generate the energy consumption rates under distinct operating conditions, such as speed, acceleration and battery level. A methodology to project the energy consumption for trip-level traffic inputs was proposed. The CART method has been applied on the training set to classify various driving conditions into finite number of clusters by their fuel and electricity consumption. In addition, LSTMs were evaluated for use in modeling. A prediction framework where Basic Safety Message data from connected vehicles was considered for predicting fuel consumption. The Wyoming connected vehicle pilot study data and a Seattle I-405 data set were investigated.

We have used CART to develop bin-based models and validated the results with AUTONOMIE generated results. The performance of CART clusters was assessed at trip level, cluster level and instantaneous level. For trip-level results, the total energy consumption by trip generated from Autonomie and CART clusters were compared using an ordinary linear regression as indicated in the figure below. For both fuel and electricity consumption, the predicted energy consumption is close to the ground-truth energy consumption with low prediction variance (represented by the shade area). The results indicated that CART clusters can predict fuel and electricity consumption within reasonable ranges at various levels.

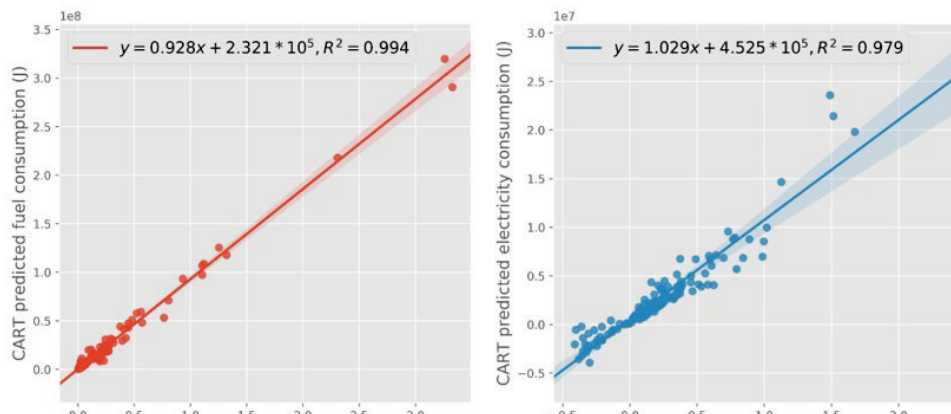


Figure VI.3.3 Comparison of Total energy consumption by trip generated by Autonomie and CART clusters

The sensitivity of CART generated clusters was assessed with respect to trip average speeds and initial SOC levels, and the results suggested that the CART generated clusters were sensitive to selected transportation parameters.

Conclusions

We have made significant progress towards our goals in the past 10 months. Our initial work to use machine learning to evaluate and predict the geospatial, temporal device data has shown promising results. Specifically, Temporal Convolution Networks had been applied and appear transferable for our initial traffic estimation problem. Automated hyper-parameter search and tuning has been developed and allow efficiencies that will be foundational to our future work. Initial efforts are underway to consider data veracity issues associated with big data feeds from a variety of mobile devices. Algorithms to detect and correct poor data quality are being developed for both ingestion at real-time and quasi real-time. Our urban simulation work has leveraged an existing code base for grid simulation and has allowed us to build urban-scale simulations of the Bay Area road network with run times on the order of minutes. We have included the SFCTA demand model that emulated 21.7M vehicle trips. An efficient vehicle routing algorithm has been integrated that will allow us to run simulations that include dynamic routing. This type of behavior is much more reflective of real-world urban dynamics. Energy modeling has been tied to the foundational simulation mechanisms and models fuel consumption using the dynamometer derived data from ANL. In addition to the initial ORNL energy modeling using CART, NREL has provided additional input to this initial model and an on-going improvement to this model is underway.

Key Publications

Conference presentations:

Cy Chan presented at IEEE ITSS, Nov 4-7, 2018 in Maui, Hawaii

Published papers:

- IEEE ITS Nov 4-7 to be published in proceedings
- Xu, Xiaodan, and H M A Aziz, (2019). An Advanced Modal-Based and Scalable Approach To Estimate Energy Consumption From Electric Vehicles. *Accepted in the Transportation Research Board Annual Meeting, 2019. Paper no. 19-05189.*

Meetings / Conferences / Other updates and highlights

- Large Scale Computing Workshop at IEEE ITS Conference, Nov 4-7, 2018
- 2018 IEEE Power and Energy Society General Meeting, August 5-10, 2018

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1. Bai, Shaojie, J. Zico Kolter, and Vladlen Koltun. "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling." arXiv preprint arXiv:1803.01271 (2018)

VII Advanced Research and Development

VII.1 Energy Impact of Connected and Automated Vehicle Technologies [DE-EE0007212]

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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 evaluates 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 most notable results of this project are summarized below

- Task 1 Instrumentation and data acquisition of energy related information
 - Collected data using the OBD-port dongles from > 500 vehicles
 - The collected data is from > 750k trips, 7.1M miles
 - Data shared within the research team, EPA, and selected UM students for research.
 - ANL researchers analyzed and used the data for their Polaris model development.
- Task 2 Display energy related information to study its influence on the driver
 - Designed human participant experiment
 - Completed all experimental data collection from 32 participants, reduced driving data by using geo-fences and conducted analysis on user acceptance and behavior measures.
 - Analysis results used to develop human driver behavior models under advisory CAV functions.
- Task 3 Travel Behavior Modeling
 - Modeled baseline activity patterns of Ann Arbor using collected vehicle trip information
 - Conducted analysis of the impact of CAVs on traffic and energy consumption
 - Studied the potential of using CAV fleet to serve the mobility of multiple families using the travel behavior information
- Task 4 System Model Development and Validation
 - Using the collected Ann Arbor travel data to calibrate a Polaris model that simulates mesoscopic traffic behavior of the city of Ann Arbor and its surroundings.
 - Embedded Energy Estimation function in POLARIS based on machine learning.
 - Simulated the energy impacts of CAV functions such as Adaptive Cruise Control, Eco-approaching, and Eco-Routing.
- Task 5 Adaptive Signal Control
 - Developed an algorithm to accurately estimate the traffic flow around intersections under low connected vehicle penetration rate

- Data collection from 6 intersections on Plymouth Rd, Ann Arbor.
- Developed an adaptive signal control algorithm and confirmed its effectiveness in simulations
- Working with several other cities including Chattanooga, TN to explore collaborative opportunities for field deployment.

Conclusions

At the initiation of this project, there are a few key gaps in understanding the potential impacts of connected and automated vehicles (CAVs) to overall energy consumption, including the lack of real field test data, the lack of a high-fidelity model, and lack of real CAV functions evaluated at a large scale (e.g., for a mid-sized city like Ann Arbor). This success of this project fills several of the data, model and CAV function gaps:

- Collected field data from > 500 vehicles, which provides the basis of vehicle trips (origin-destination, travel speed, time) and energy consumption information. At the conclusion of this project, we estimate the total amount of data available will be more than 8 million miles.
- The field data is used by the Argonne National Lab to develop and calibrate their Polaris model for Ann Arbor. The model has shown to match the travel pattern of the City accurately.
- By collaborating with University of Michigan researchers the travel data has also been used to develop and calibrate a SUMO model (an open-source traffic simulation platform).
- Two representative CAV functions have been analyzed using the Ann Arbor data/model. The Eco-approaching algorithm using real human driver data collected from the Plymouth Corridor of Ann Arbor shows very encouraging (albeit idealized) potential in reducing fuel consumption by >30%. The eco-routing algorithm evaluated in the Ann Arbor-wide traffic simulation for 800 vehicle trips using the SUMO model has demonstrated 6% fuel consumption reduction.

While the work by the team over the last three years has addressed a few key gaps, many more challenges remain to explore the full potential of CAVs.

Key Publications

1. Di, X., Liu, H.X., Ban, X., Yang, H., 2016. Ridesharing User Equilibrium and Its Implications for High-Occupancy Toll Lane Pricing, *Transportation Research Record*, 2667, doi: 10.3141/2667-05.
2. Zheng, J. and Liu, H.X., 2017. Estimating traffic volumes for signalized intersections using connected vehicle data. *Transportation Research Part C: Emerging Technologies*, 79, pp.347-362.
3. Feng, Y., Yu, C., Liu, H.X., Spatial-temporal Intersection Control in a Connected and Automated Vehicle Environment. *Transp. Res. Part C Emerg. Technology*
4. 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*.
5. Feng, Y., Zheng J., and Liu, H.X., A Real-time Detector-free Adaptive Signal Control with Low Penetration of Connected Vehicles. *Transportation Research Record*.
6. Di, X., Zhao, Y., Zhang, Z., and Liu, H., Data-Driven Similarity Analysis for Activity-based Travel Demand Modeling, Submitted to 2017 TRB Annual Meeting for Presentation.
7. Huang, X. and Peng, H., 2017, May. Speed trajectory planning at signalized intersections using sequential convex optimization. In *American Control Conference (ACC)*, 2017(pp. 2992-2997). IEEE.
8. Di, X., Liu, H.X., Ban, X., Yang, H., 2016. Ridesharing User Equilibrium and Its Implications for High-Occupancy Toll Lane Pricing, *Transportation Research Record*, 2667, doi: 10.3141/2667-05.

9. Huang, X. & Peng, H., 2018. Eco-Routing based on a Data Driven Fuel Consumption Model. To appear in 14th International Symposium on Advanced Vehicle Control, AVEC'18.
10. Huang, X. & Peng, H., 2018. Efficient Mobility-on-Demand System with Ride-Sharing. Submitted to The 21st IEEE International Conference on Intelligent Transportation Systems.
11. Zheng, J. and Liu, H.X., 2017. Estimating traffic volumes for signalized intersections using connected vehicle data. *Transportation Research Part C: Emerging Technologies*, 79, pp.347-362.
12. Feng, Y., Yu, C. and Liu, H.X., 2018. Spatiotemporal Intersection Control in a Connected and Automated Vehicle Environment. *Transportation Research Part C: Emerging Technologies*, 89, pp.364-383.
13. Yu, C., Feng, Y., Liu, H.X., Ma, W. and Yang X., 2018. Integrated optimization of traffic signals and vehicle trajectories at isolated urban intersections. *Transportation Research Part B: Methodological*. (In Press)
14. Feng, Y., Zheng, J. and Liu, H.X., 2018. A Real-time Detector-Free Adaptive Signal Control with Low Penetration of Connected Vehicles. *Transportation Research Record*. (In Press)

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VII.2 Boosting Energy Efficiency of Heterogeneous Connected and Automated Vehicle (CAV) Fleets via Anticipative and Cooperative Vehicle Guidance (Clemson University)

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End Date: August 31, 2019

Project Funding: \$701,952

DOE share: \$592,099

Non-DOE share: \$109,853

Project Introduction

This project introduces novel anticipative car following and lane selection schemes for Connected and Automated Vehicles (CAVs). Our control schemes benefit from collaboration and information exchange between CAVs to save energy, reduce braking, and harmonize traffic. The proposed schemes will be implemented in traffic microsimulations at different levels of CAV penetration to analyze energy saving benefits. We will also create a Vehicle-in-the-Loop (VIL) testbed to demonstrate the benefits to real CAVs driven on a test-track.

Clemson has partnered with Argonne National Laboratory to integrate the vehicle guidance algorithms with Autonomie, Argonne's detailed vehicle energy utilization simulation software. Clemson has partnered with PTV to incorporate the proposed algorithms in their state of the art traffic micro-simulation tool, Vissim. Clemson also has partnered with International Transportation Innovation Center (ITIC) to conduct experiments for evaluating the proposed technical approach with novel co-simulations of traffic and physical automated vehicles on a test track in Greenville, South Carolina.

Objectives

Figure VII.2.1 shows the breakdown of the project into three main objectives over the 2 YEAR period of the project:

1) *Developing Anticipative Vehicle Guidance Algorithms.* The relevant milestones are as follows:

- Perception and Prediction of Motion of Surrounding Vehicles: Demonstrate >50% success rate in anticipating the position of a vehicle within a 10-meter radius of its position, 5 seconds in advance.
- Car following and Lane Selection Algorithm Design: Incorporate anticipation in car-following and lane selection strategy to demonstrate >5% efficiency gain in mixed traffic with 30% CAV penetration.
- Custom Code Generation for PTV Vissim Traffic Microsimulation.

2) *Traffic Microsimulations.* The relevant milestones are as follows:

- Detailed Energy Evaluation: Use high-fidelity powertrain models of heterogeneous vehicles to demonstrate >5% (10%) average efficiency gain in mixed traffic for CAV penetration >30% (60%).

3) *Experimental testing via VIL platform.* The relevant milestones are as follows:

- One experimental CAV in VIL Testbed: Complete vehicle instrumentation, test-track communication setup, and integration with micro simulation environment. Demonstrate at least >5% energy efficiency.
- Two experimental CAVs in VIL Testbed: Demonstrate stable co-simulation of 2 experimental vehicles and <10 virtual vehicles and document >5% average energy efficiency gain for the entire fleet.
- VIL simulations for multi-lane scenarios: Demonstrate stable co-simulation during lane change operation and document >5% additional average efficiency gain resulting from collaborative driving.

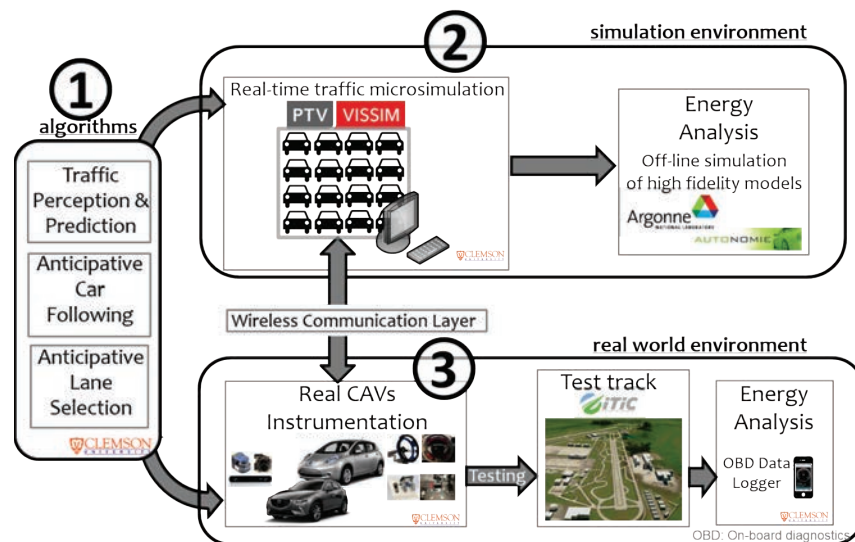


Figure VII.2.1 The project breakdown into three main objectives.

Approach

Eco-Driving Algorithms

A combined probability modeling and Model Predictive Control (MPC) system is employed to boost the energy efficiency of CAVs. MPC consumes a preview of disturbances and optimizes a modeled system over a finite time horizon. In heterogeneous traffic, CAVs using MPC communicate their intentions to other CAVs. When

interacting with conventional vehicles, a CAV must predict using current and historic sensed data as shown in Figure VII.2.2.

Anticipative Car Following Scheme

In car following, the probability that the preceding vehicle (PV) will transition to a given acceleration state at each prediction step is determined by counting past observations. This model yields the PV's expected acceleration commands, which in turn result in a position trajectory for the MPC objective. To prevent collisions during PV braking, a worst-case model of PV motion is used in the MPC constraints. Given a preview, MPC then minimizes a weighted sum of squared position gap error and acceleration. This velocity-smoothing approach improves energy efficiency.

Experimental Prediction of Surrounding Vehicles Motions

To verify that the proposed prediction algorithms are feasible in a public-road implementation, similar models were implemented and validated on historical bus data from the Tiger Commute system. Changes in velocity were predicted using a Markov model with direction, location, time of day, and current state as inputs.

Anticipative Lane Selection Scheme

The lane decision algorithm presented in [4] was modified to track a desired velocity of the ego vehicle, eliminating the need for a tripped lane change when the velocity moved outside of a given bound. This generated another issue where if there was no lane available with a reference speed equal to or higher than the ego vehicle desired velocity, the ego vehicle would tend to travel between lanes. To prevent this from happening an additional term was added to the cost function to penalize choosing multiple lanes at once and rules were added to the reference speed assigner to modify the ego vehicle desired velocity as well. Further improvements were made to the lane decision control framework. The complete framework may be found in [5].

Work has also occurred in implementing the MPC based lane decision framework within the traffic simulator Vissim. Initially a simplified MPC that tracked the center of a lane and a reference velocity using the ACADO toolkit [6] was implemented as an external driver model in Vissim, in order to prove the compatibility between the solver and Vissim. Next, progressively more complex controllers were implemented in Vissim, beginning with one vehicle being controlled with an obstacle avoidance controller, then one vehicle being controlled with the lane decision MPC, and finally multiple vehicles being controlled with the lane decision MPC.

Custom Code Generation for PTV Vissim Traffic Microsimulation

To study the impact of CAVs in the presence of human-driven fleets of vehicles, the traffic microsimulation software Vissim, is utilized. We embed physical vehicles into this environment interacting with virtually driven vehicles. Several steps were taken to import CAVs into Vissim: 1) Program the car-following and lane selection algorithms and optimization into C++ code, 2) Compile a Dynamically Linked Library (DLL), which binds to Vissim and gives access to our custom control code, 3) Wrap the Component Object Model (COM) interface for Vissim into an easily accessible library for controlling Vissim simulations and automating test scenarios, and 4) Conduct simulations of varying densities of traffic and varying densities of CAVs in a highway environment.

Experimental Verification in Vehicle-in-the-Loop Testbed

To validate the effectiveness of the proposed anticipative and cooperative vehicle guidance algorithms in realistic contexts, we have constructed a vehicle-in-the-loop testbed where two real connected automated vehicles interact with virtual traffic in real time. Towards this goal, two real vehicles are retrofitted into automated and connected vehicles. One gasoline engine car (Mazda CX-7) and one fully electric car (Nissan Leaf) are adapted to validate and compare the effectiveness of our algorithm on different powertrain configurations. These two vehicles will have the ability of communicating with each other and also can

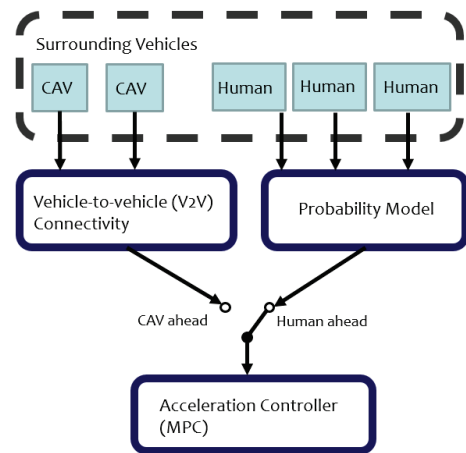


Figure VII.2.2 Block diagram of the major motion planning algorithm components.

communicate with virtual vehicles in the Vissim simulation to share driving information. They can drive in automated modes on a test track to execute the motions generated from our algorithms while communicating with each other and virtual vehicles. At the same time, the fuel/electricity consumption will be recorded and compared with the fuel/electricity consumption of human driving cycles under the same driving situations.

Energy consumption measurement for experimental CAVs

The energy consumption of experimental CAVs are currently measured via On-Board Diagnostics (OBD-II) port of the vehicles. A smart-phone iOS application, already implemented in our group [7], [8], can access the OBD port of both vehicles and estimate the real-time energy consumption of the vehicle. As shown in Figure VII.2.3, the implemented iOS application can connect to commercial WiFi OBDII readers supporting ELM327 chip. If we find the OBD-II readings are insufficient we will use more advanced methods for recording energy consumption during YEAR 2.

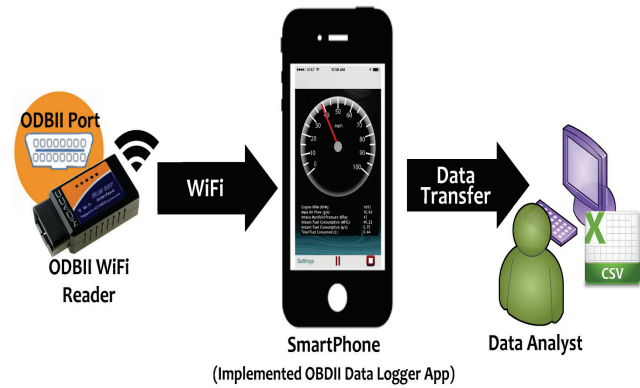


Figure VII.2.3 Functional architecture of the developed iOS OBD Logger App [7], [8].

Analysis of propagation loss and reliability in wireless communication

In CAV networks, radio wave attenuation should be modeled before claiming the achieved performance. Significant radio signal attenuation could happen due to the distance, multipath signal fading, and shadowing [1]. To realize the impact of path loss and fading, we use the following generalized equation $P_{Rx}(d) = P_{Tx} + G - \sum PL(d)$ where, $P_{Rx}(d)$ is the calculated received power of receiver Rx , for distance d from transmitter Tx ; G is the antenna gain. $PL(d)$ contains the path loss components of large-scale path loss and fading, and of deterministic obstacle shadowing, or of stochastic fast fading. We adopt four different loss models: random loss model as a representative of abstract loss model, long distance loss model [3] as a representative of deterministic loss model, LOS (Line-of-sight)/OLOS

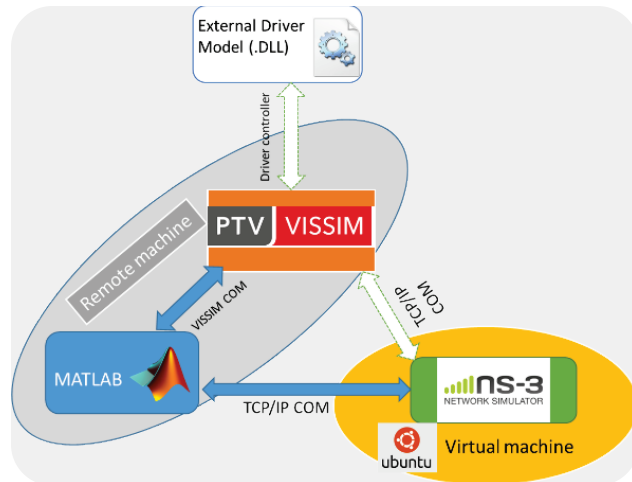


Figure VII.2.4 The wireless communication simulator.

(Obstructed-LOS) loss model as a representative of empirical loss model and Friis-Nakagami [2] as a representative of joint deterministic and stochastic fading model. As shown in Figure VII.2.4, the vehicles are simulated using PTV Vissim, and the communication network is simulated by ns-3 (network simulation – 3). MATLAB is also used for setting up traffic parameters and setting real-time communication through TCP/IP.

Results

Car Following Simulations

Anticipative eco-driving controllers were prototyped in a MATLAB-based multi-agent simulation environment. A velocity profile is imposed on the lead vehicle as a boundary condition and energy benefits are evaluated for the following vehicles. Early simulations with homogenous strings showed that the among the FTP, US06, and HWFET cycles, the US06 represented a middle ground for energy benefits. A more detailed study using mixed CAV and conventional traffic with both heavy and passenger vehicles showed 1.4 to 1.9% fuel economy improvement per 10 percentage point increase in CAVs (Figure VII.2.5) when the lead vehicle followed the US06.

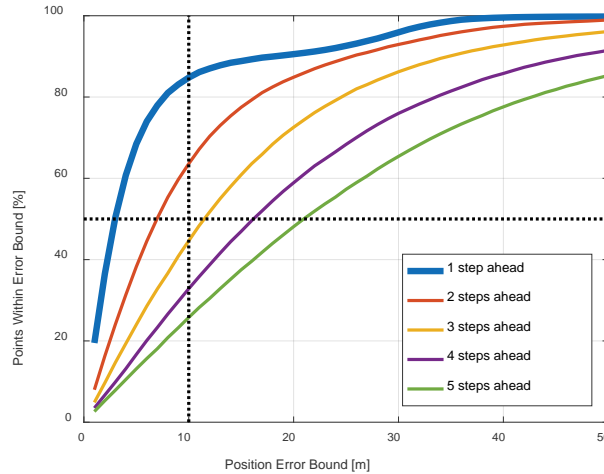


Figure VII.2.6 Position prediction errors in the Tiger Commute bus dataset.

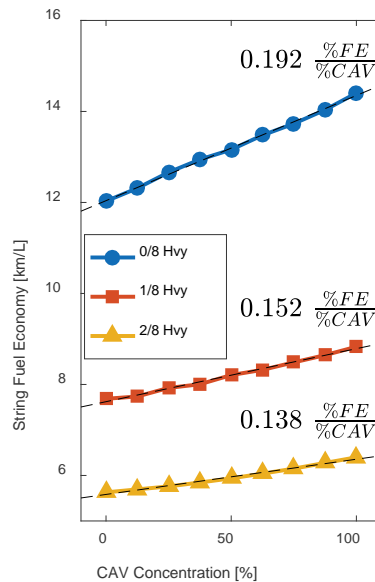


Figure VII.2.5 Fuel economy benefits of CAVs in multi-agent mixed traffic MATLAB simulations.

Experimental Prediction of Surrounding Vehicles Motions

The system was evaluated on a subset of the bus data that was not used for training. 5s ahead, 85% of predictions were within 10 m of the ground truth. Accuracy at other time ranges is shown in Figure VII.2.6.

Anticipative Lane Selection Scheme

Monte-Carlo simulations of specific scenarios were completed in MATLAB with one MPC vehicle and precomputed object vehicle trajectories. Noise was injected into the state measurements and control inputs of the MPC vehicle and into the measurements of the object vehicle. In the first simulated scenario, the ego vehicle is traveling in the center lane and about to pass a slower moving object vehicle 1 (OV1) on its right, when a faster moving OV2 passes the ego vehicle on the right and cuts in between. At this point the ego vehicle must evasively maneuver to the left lane to avoid a collision. This resulted in a probability of collision on the order of 10^{-18} and a plot of the trajectory and control inputs may be found in Figure VII.2.7. The second simulated scenario consists of a 4 lane road with 5 OVs, not depicted here. Detailed information on the complete lane decision control framework is presented in [5]. There is still work to be done aligning the MPC and lateral dynamics models. Figure VII.2.8



Figure VII.2.8 Vissim with multiple MPC vehicles (orange), and human controlled traffic (black)

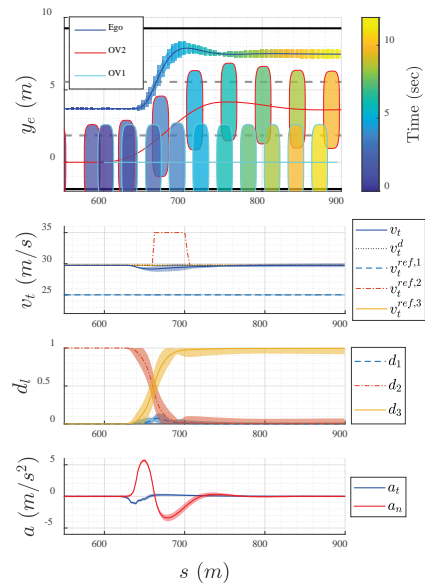


Figure VII.2.7 Scenario 1 trajectory, velocity, lane decision variable, and acceleration plots.

Custom Code Generation for PTV Vissim Traffic Microsimulation

We have been successful in building the software necessary to complete CAV microsimulations in Vissim. We successfully followed the process of incorporating MPC car-following and lane selection algorithms into Vissim vehicles, vary Vissim traffic conditions, and process data into preliminary results. We found preliminary results in the improvement of fuel economy and space occupied on the road, given increasing densities of CAVs. These were consistent with our Matlab microsimulations. Our preliminary results also showed an increase in travel times of vehicles given an increasing density of CAVs; this suggests further tuning our controller to interact with human-driven vehicles. These results further motivate direction of the project in Year 2.

Instrumenting and Automating the experimental CAVs

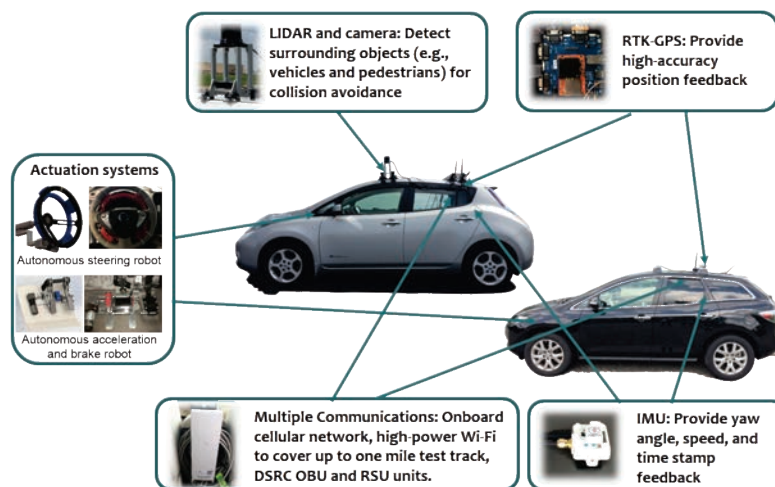
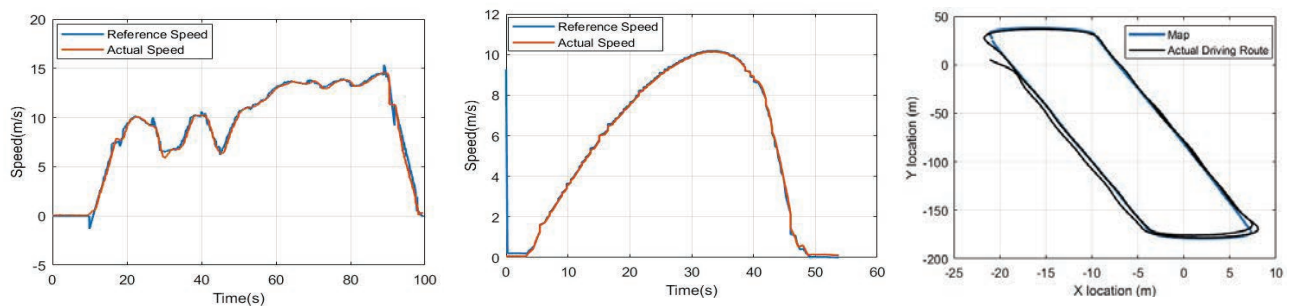


Figure VII.2.9 Retrofitted Vehicles by Self-Developed Robotic AutoDrive System

We have used the self-developed Robotic AutoDrive System to retrofit two vehicles (Mazda CX-7 and Nissan Leaf) and turn them into an automated-driving capable vehicles, as shown in Figure VII.2.9. An automated driving robot is designed for both vehicles. It utilizes a DC motor to actuate the steering wheel and another DC motor to actuate both the brake and the throttle pedals. The Nissan, which is supposed to drive behind the Mazda, is also equipped with a Quanergy M8 3D LIDAR to ensure safety. Sensor fusion has been performed onboard to calculate the accurate location, orientation, and speed of vehicles in real time. The control of the throttle and brake pedals is achieved by a combination of a calibrated response function and a PID controller. The calibrated response function is obtained by fitting the data collected from vehicle dyno tests. Since the responses of throttle and brake pedal positions to actual acceleration and deceleration are highly non-linear, using a PID controller within entire operating range will result in large errors, overshoots and oscillations. The calibrated response function adjusts the positions of throttle and brake pedals to achieve the expected speed and acceleration. Figure VII.2.10 shows the performance of the speed controller on the Nissan Leaf. The speed tracking performance is sufficient for our tests and the velocity tracking error is about $\pm 0.1\text{m/s}$.



a. IM240 cycle speed tracking b. Car following control speed tracking c. Waypoint tracking performance

Figure VII.2.10 Performance of (a-b) speed tracking and (c) trajectory tracking controllers

A trajectory tracking controller has been designed and implemented to make the vehicle track a desired trajectory. A bicycle vehicle model and a pure pursuit controller [10] are employed to enable the controller to generate the desired vehicle speed and steering based on the vehicle velocity and heading feedback from the fusion of onboard sensors and location information from the RTK-GPS. The speed control is realized using the throttle and brake controller and the steering control is realized using a low-level PID controller. Figure VII.2.10(c) shows that the trajectory tracking controller follows the desired trajectories well.

We’ve also finished the instrumentation of the second vehicle and started the tuning of its robotic control system. We’ve finished the throttle and brake pedal control calibration through dyno tests. We will soon take the second vehicle to the test track for further testing and tuning.

Vehicle-in-the-Loop Simulation Setup

Vehicle in the loop test with virtual vehicle generated by Vissim has been conducted. The physical vehicle was able to respond to the virtual surrounding vehicles generated by Vissim correctly and Vissim could visualize the physical vehicle in the simulation environment and react to it. Figure VII.2.11 shows an example visualization.



Figure VII.2.11 Physical vehicle embedded in virtual

OBD-based Energy Consumption Measurement and Data Logging

We’ve also managed to read out energy consumption through OBD port and the reporting rate is 2Hz. Our developed iOS application explained in the previous section was originally compatible with 29-bit CAN protocol (ISO 15765-4) and, now, it is extended to read and collect 11-bit CAN protocol needed for this

project. The OBD Log iOS Application is also improved to read the OBD port of our battery electric experimental CAV (Nissan Leaf 2011). Unlike our combustion test vehicle, the specification of the packets sent to the OBD port of our electric vehicle are not published by the vehicle manufacturer. The reason is that the electric car manufacturers have not yet established a standard for messages exchanged in CAN bus [9].

Vehicle-in-the-loop (VIL) Communication Setup

Communication between the physical vehicle and the computer that runs Vissim simulation has been tested using both cellular and Wi-Fi connections. The cellular communication is stable. Although the Wi-Fi connection also works, its stability still needs to be improved due to the large communication range. These two communication methods will be used as alternatives before the DSRC system is completely ready for use. We send and receive the information through a User-Datagram Protocol or UDP unconnected datagram sockets. We serialize the data, using Google Protocol Buffers. The data exchanged between our physical vehicles and Vissim lies in four categories: 1) Subscription/Unsubscription Message, 2) Vehicle to Vissim Message, 3) Vissim to Vehicle Message, and 4) Vehicle to Vehicle Message.

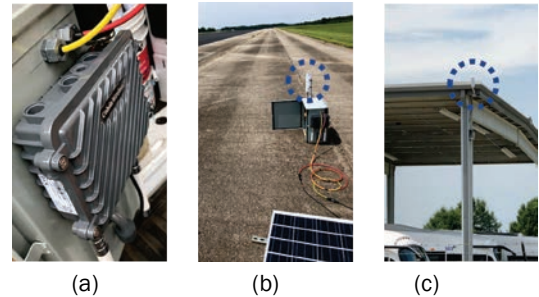


Figure VII.2.12 (a) Our road-side unit (RSU) for DSRC (b) the RSU box powered by solar panels at test track (c) the direct antenna communicating with the RSUs at the test track.

ITIC negotiated with the equipment and service providers and made a final decision to implement 2 DSRC radios on the testbed. The DSRC road-side units (RSUs) are solar-powered, as shown in Figure VII.2.12 (a-b). In this configuration, the DSRC radios are connected to the secure ITIC network via directional antennas shown in Figure VII.2.12(c).

Impact of path loss on Communication Packet Delivery Ratio (PDR) and Reliability

The performance has been realized both by the network-level metric, such as packet delivery ratio (PDR) and application-level metric, such as T-window reliability. PDR is the ratio of the number of received packets to the expected received packets in a given range. T-window reliability is the probability of successfully receiving at least one packet from a certain transmitter to a certain receiver within a time window, T-window.

Figure VII.2.13 and Figure VII.2.14 show with no-loss model, PDR is the maximum. PDR starts dropping only after 600m communication distance. However, this is not the case, while path loss model is considered. The Random loss model has around 38% more packet drops than no-loss model. PDRs of long distance loss model and Friis-Nakagami have the identical results (around 50% more packet drops than no-loss model). However, LOS/OLOS model has the maximum PDR drops. With 400m communication range, LOS/OLOS model has the 72%, 56%, 46%, and 47% more packet drops than respectively, no-loss model, random loss model, long distance model, and Friis-Nakagami model. These results reflect that without considering a realistic path loss model, the claimed performance is superficial and may provide inconsistent results. A similar performance difference is also observed for the T-window reliability measurement. Increasing T-window, yields the same PDR but increases the reliability for all the approaches (Figure VII.2.14).

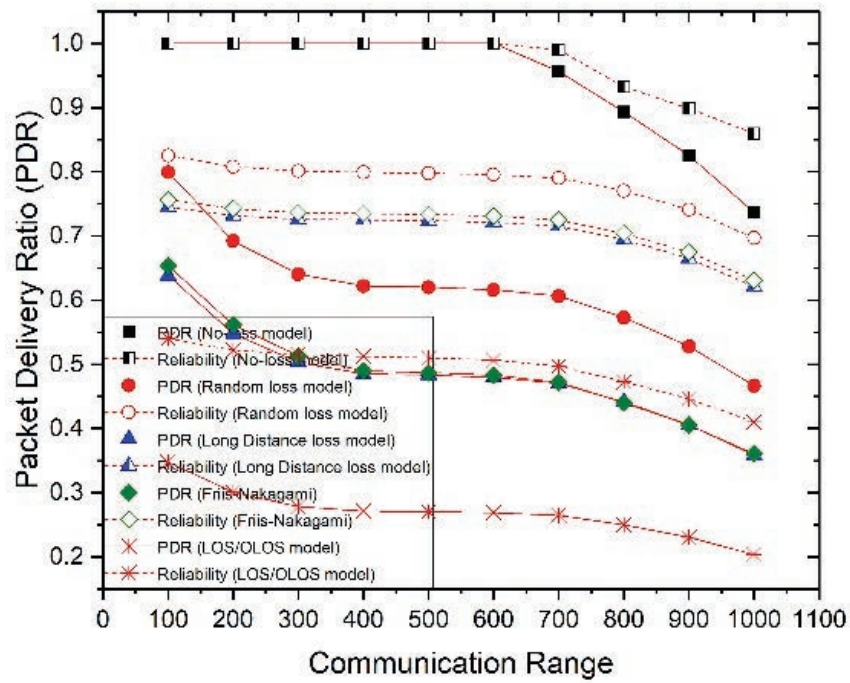


Figure VII.2.14 Impact of path loss on PDR and reliability for T-window=300msec.

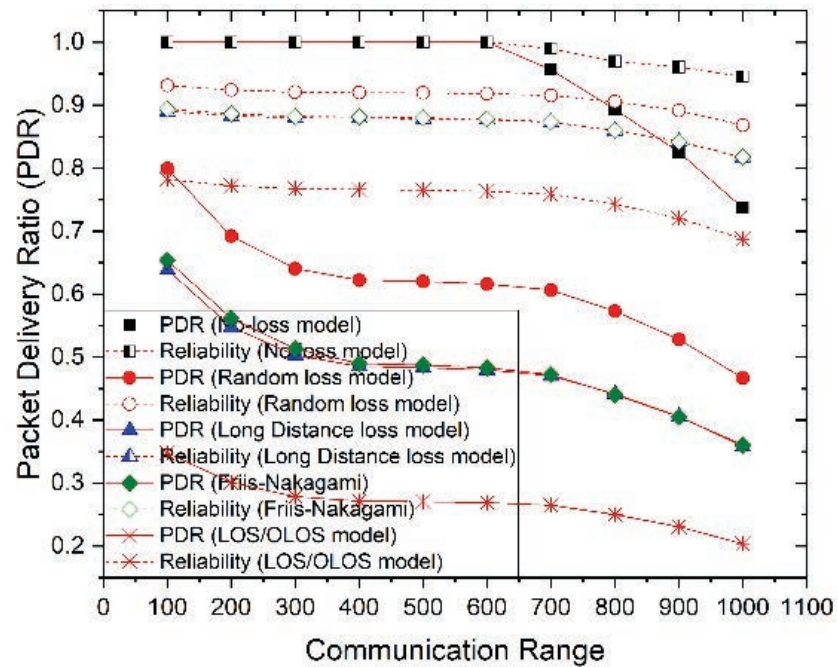


Figure VII.2.13 Impact of path loss model on PDR and reliability with T-window=1sec.

Impact of path loss model on latency

Figure VII.2.15 shows the latency for per received packet/instance. Clearly, while considering the received packets, the latency is negligible (around 2 msec). However, for received instances, the latency increases. Under different T-window values, no-loss model has the lowest latency and LOS/OLOS model has the highest latency. However, the maximum latency with the LOS/OLOS model under T-window value is below 30 msec, which is well below the latency requirement for VSC applications (100 msec).

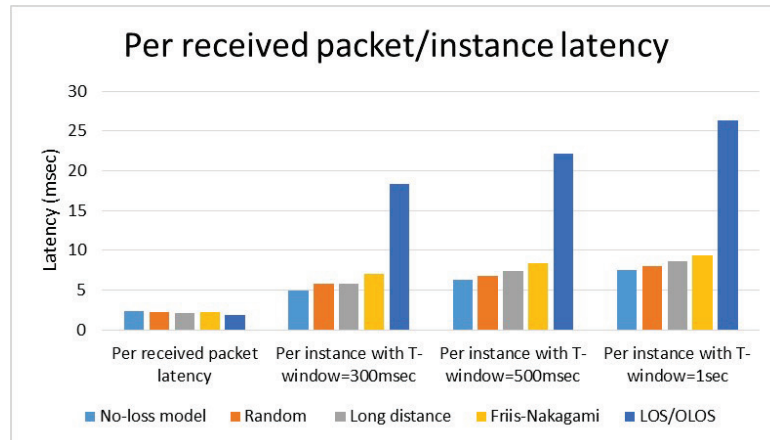


Figure VII.2.15 Per received packet/instance latency.

For some time-sensitive safety applications (e.g., T-window=300 msec), the achieved T-window reliability is as low as 50% under LOS/OLOS model with the current DSRC based broadcasting, which is not satisfactory at all. Hence, there is an urge to improve the reliability. One possible way to improve the PDR and reliability is using opportunistic vehicle-assisted or dedicated RSU-assisted selective relaying.

Conclusions

Prediction results using Tiger Commute bus data and early control simulation results in MATLAB meet our milestones. Our work will continue to finalize the implementation of the lane decision MPC within Vissim and obtain fuel efficiency results from simulations with different penetrations of CAVs. We successfully followed the process of incorporating MPC car-following algorithms into Vissim vehicles. A workflow has been established to use results from Vissim micro-simulation as inputs to Autonomie. This process, which uses distributed computing techniques, allows to quickly generate accurate energy consumption results for particular scenarios. The retrofitting of the Nissan Leaf is finished, and it has been tested together with Vissim simulation. The Nissan Leaf is ready for energy efficiency test. The retrofitting of the Mazda CX-7 has progressed as planned. It will be ready soon for fuel efficiency experiments. Our iOS application is now capable of collecting data from OBD ports of our experimental CAVs. The energy consumption of the electric test vehicle will be measured using the OBD data of the battery. We have studied the impact of path loss models in radio propagation in urban connected and automated vehicle (CAV) networks. The impact has been realized by both the network-level and application-level performance metrics.

Key Publications

1. R. Austin Dollar, and Ardalan Vahidi. "Quantifying the impact of limited information and control robustness on connected automated platoons." In Intelligent Transportation Systems (ITSC), 2017 IEEE 20th International Conference on, pp. 1-7. IEEE, 2017
2. R. Austin Dollar, and Ardalan Vahidi. "Efficient and Collision-Free Anticipative Cruise Control in Randomly Mixed Strings." In print, IEEE Transactions on Intelligent Vehicles (2018).

3. R. Austin Dollar, and Ardalan Vahidi. "Predictively Coordinated Vehicle Acceleration and Lane Selection Using Mixed Integer Programming." In Proceedings of the ASME DSCC, 2018.
4. X. Wang, L. Guo and Y. Jia, "Human Intervention Detection on a Retrofit Steering Actuation System in Autonomous Vehicles," SAE Technical Paper, 2018. (Trevor O. Jones Outstanding Paper Award)
5. X. Wang, L. Guo and Y. Jia, "Online Sensing of Human Steering Intervention Torque for Autonomous Driving Actuation Systems," IEEE Sensors Journal, vol. 18, no. 8, pp. 3444-3453, 2018.
6. G. G. Md Nawaz Ali, and Beshah Ayalew, "Analysis of propagation loss and reliability in urban/sub-urban vehicular cyber-physical system", in progress.

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8. OBD Log iOS Application introduction, available online: <https://youtu.be/7zWhUk7hEZQ>
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10. Coulter, R. Craig. Implementation of the pure pursuit path tracking algorithm. No. CMU-RI-TR-92-01. Carnegie-Mellon UNIV Pittsburgh PA Robotics INST, 1992.

VII.3 Developing an Eco-Cooperative Automated Control System (Eco-CAC)

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Start Date: October 1, 2017

End Date: June 30, 2019

Project Funding: \$1,675,265

DOE share: \$1,507,197

Non-DOE share: \$168,068

Project Introduction

The transportation sector accounts for 69% of the nation's petroleum consumption and 33% of the nation's CO₂ emissions. Consequently, any reductions in the energy consumed by the transportation sector will have significant environmental benefits. Connected Vehicle (CV) systems comprise sets of applications that connect vehicles to each other and to the roadway infrastructure using vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, collectively known as V2X. While Automated Vehicles (AVs) offer enhanced operation of individual vehicles, CVs produce cooperative, network-wide benefits through the exchange of information. These new technological advancements have the potential to drastically improve the efficiency and sustainability of our transportation system. We are taking a revolutionary approach to developing a next-generation, vehicle dynamics (VD) Connected Automated Vehicle (CAV) system that builds on existing CAV technologies to reduce the energy/fuel consumption of internal combustion engine vehicles (ICEVs), battery-only electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs).

Objectives

The main project objective is to substantially reduce vehicle fuel/energy consumption by integrating vehicle control strategies with CAV applications. Specifically, are developing a novel integrated control system that (1) routes vehicles in a fuel/energy-efficient manner and balances the flow of traffic entering congested regions, (2) selects vehicle speeds based on anticipated traffic network evolution to avoid or delay the breakdown of a sub-region, (3) minimizes local fluctuations in vehicle speeds (also known as speed volatility), and (4) enhances the fuel/energy efficiency of ICEVs, BEVs, HEVs, and PHEVs.

Approach

We are taking a revolutionary approach to developing a next-generation CAV system (Figure VII.3.1) that builds on existing CAV technologies to reduce the energy/fuel consumption of ICEVs, BEVs, HEVs, and PHEVs. The development of the Eco-Cooperative Automated Control System (Eco-CAC) system will involve the following key steps and components:

1. Develop a CV eco-routing controller that can be used for various vehicle types. This unique eco-router will use a dynamic feedback controller, employ key link parameters that capture the entire drive cycle, compute vehicle-specific link energy functions using these link parameters, and compute user- and system-optimum routings.
2. Develop a speed harmonization (SPD-HARM) controller that regulates the flow of traffic approaching network bottlenecks identified using the Network Fundamental Diagram (NFD). This controller will be fully integrated with the vehicle router, resulting in a unique strategic controller that can route traffic away from congested areas and regulate the flow of traffic entering congested areas using gating techniques.
3. Develop a multi-modal (ICEV, BEV, PHEV, and HEV) Eco-CACC-I controller that computes and implements optimum vehicle trajectories (ICEVs, BEVs, PHEVs, and HEVs) along multi-intersection roadways within CAVs considering dynamic vehicle queue predictions.
4. Develop an Eco-CACC-U controller that provides local longitudinal energy-optimal control in consideration of homogenous and non-homogeneous vehicle platooning of ICEVs, BEVs, PHEVs, and HEVs.

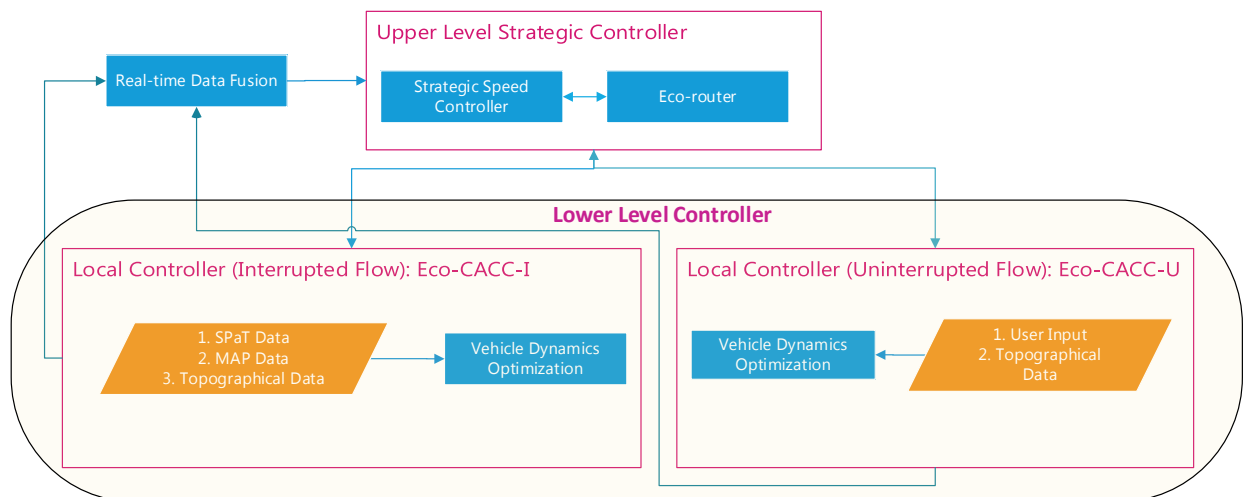


Figure VII.3.1 Proposed Eco-CAC system

At the upper level, the strategic controller (eco-router and strategic speed controller) will compute the energy/fuel-optimum route and vehicle optimum speeds (upper and lower bounds) required to regulate the flow of traffic approaching downstream sub-networks and/or bottlenecks, thus preventing or delaying the breakdown of traffic flow and mitigating traffic congestion. This strategic controller will extend traditional eco-routing and SPD-HARM systems beyond the currently used isolated control to a fully integrated, network-wide controller. The eco-router within the strategic controller will develop optimum eco-routes using a feedback linear programming optimization controller. Unlike a predictive controller, a feedback controller does not require a link-specific analytical fuel consumption function, which is typically difficult to develop, inaccurate, and not vehicle-specific. Instead, the eco-router controller uses information shared by other CVs. In addition, an SPD-HARM controller will be developed and integrated with the eco-router to regulate the traffic flow approaching transportation bottlenecks using a bi-level and reinforced learning controller. At the lower level, a VD controller will operate along the routes and within the speeds recommended by the strategic controller to compute energy-efficient vehicle speeds based on local conditions using two local controllers: an Eco-CACC-I and an Eco-CACC-U controller. The Eco-CACC-I controller will compute energy-optimum vehicle trajectories through signalized intersections (i.e., interrupted flow conditions) using traffic count and

signal phase and timing (SPaT) data. The Eco-CACC-U controller will develop fuel/energy efficient platooning strategies along uninterrupted road facilities. The VD lower-level controller will use the planned vehicle routes and trajectories to anticipate the vehicle operational mode and compute the optimum VD strategies. The fully functional Eco-CAC system will be implemented in a traffic simulation environment so that it can be tested at a network level. The proposed CAV applications, testing parameters, and validation methods will be used to quantify the Eco-CAC system benefits.

Results

For Task 1, the team developed a new power-based microscopic HEV fuel/energy consumption model that can be incorporated in various transportation applications, including microscopic traffic simulation models, in-vehicle and mobile eco-driving apps, and CV applications. The developed HEV model will be utilized for Eco-CAC applications. The model estimates the energy consumption based on driving dynamics using instantaneous vehicle speed, acceleration, and roadway grade levels, and does not rely on engine efficiency maps. Figure VII.3.2 illustrates the test vehicle's measured and estimated instantaneous fuel consumption rate for four different driving cycles. As illustrated in the figure, the results clearly demonstrate a good agreement between the instantaneous fuel consumption estimates and laboratory measurements.

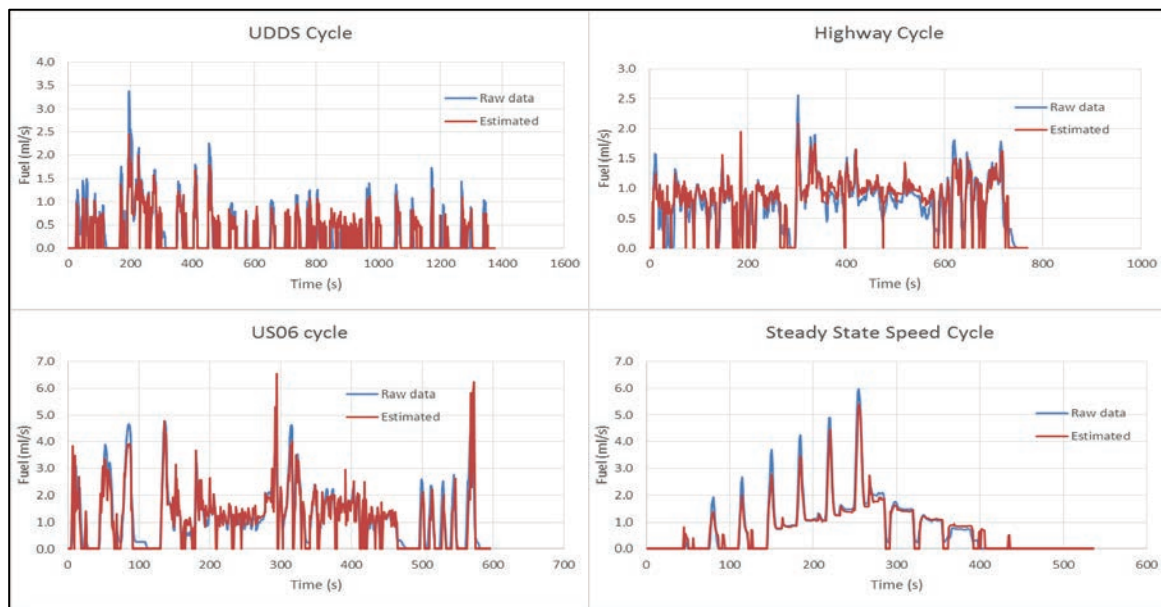


Figure VII.3.2 HEV fuel consumption estimation

For Task 2, the team developed and tested an NFD-based Proportional Integral (PI) speed controller. Procedures to estimate the NFD from CAV data were also developed. The controller was implemented on a grid network representative of a typical downtown area. Gating on the edges of the protected network in combination with fixed-time traffic signal control was compared to a base non-gated protected control considering a fixed plan, phase split traffic signal control, and phase split with cycle length optimization. The results show substantial improvement in terms of travel time, delay reduction, and fuel consumption. Specifically, on average, a 12.3% reduction in travel time, a 22.17% reduction in delay, and a 9.06% reduction in fuel consumption levels was observed.

The team tested the NFD for a selected network. The results indicate that fixed plan, phase split, phase split with cycle length optimization were unable to prevent congestion from occurring. In particular, these controls create delay and increase travel time. On the other hand, activating the proposed gating controller resulted in a noticeable difference. The network is prevented from entering the congested regime and remains operating at capacity (i.e., the highest possible throughput of the network), as illustrated in Figure VII.3.3.

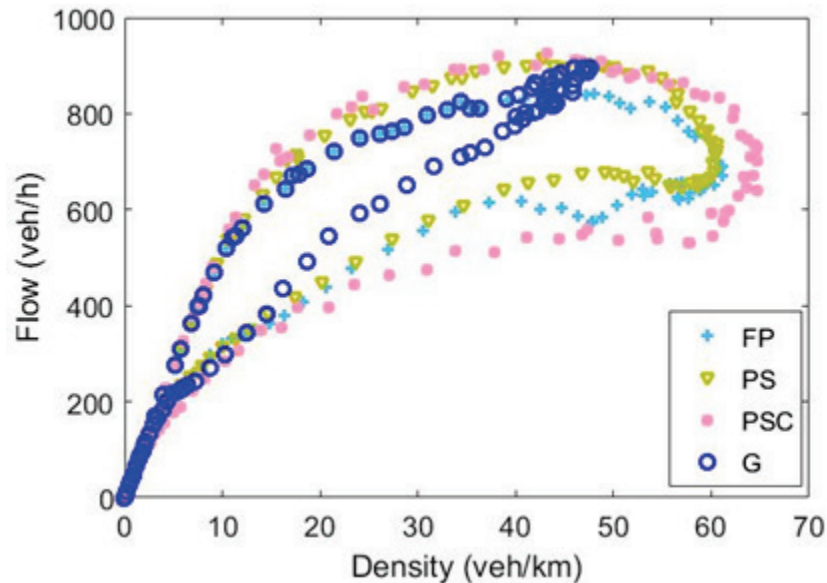


Figure VII.3.3 NFD for the protected network – fixed plan (FP), phase split (PS), phase split with cycle length (PSC), gating (G)

For Task 3, the team developed a preliminary BEV Eco-CACC-I controller for a single signalized intersection without the consideration of queue impacts. The optimal solutions were analyzed by testing the proposed BEV Eco-CACC-I controller using electric vehicles with different engine power ratings under various speed limits, signal timings, and road grades. Figure VII.3.4 illustrates sample simulation results for a 3% uphill road section using the BEV controller. The study found that the optimal solutions for BEV and ICE vehicles are very different. For a downhill roadway, the BEV requires longer deceleration time to accumulate more regenerative power to minimize the overall energy consumption in traversing the intersection. Alternatively, the ICE vehicle needs the opposite, requiring a maximum deceleration level (minimum deceleration time) to minimize the overall energy consumption. For the uphill direction, the BEV needs the minimum deceleration time to traverse the approach stop line at maximum speed, allowing it to save a lot of energy consumption while accelerating back to the roadway speed limit downstream of the intersection. Alternatively, the optimum ICE vehicle deceleration level to minimize the overall energy consumption is typically in the mid-range. The comparison results indicate the energy-optimum solution for BEVs is different from the solution for ICE vehicles, due to the fact that different types of vehicles use different approaches to consume energy. The findings in the case study also prove that previous studies, which only considered the optimization of acceleration/deceleration and ignored the specific vehicle energy model, cannot correctly compute the energy-optimal eco-driving solution for different types of vehicles.

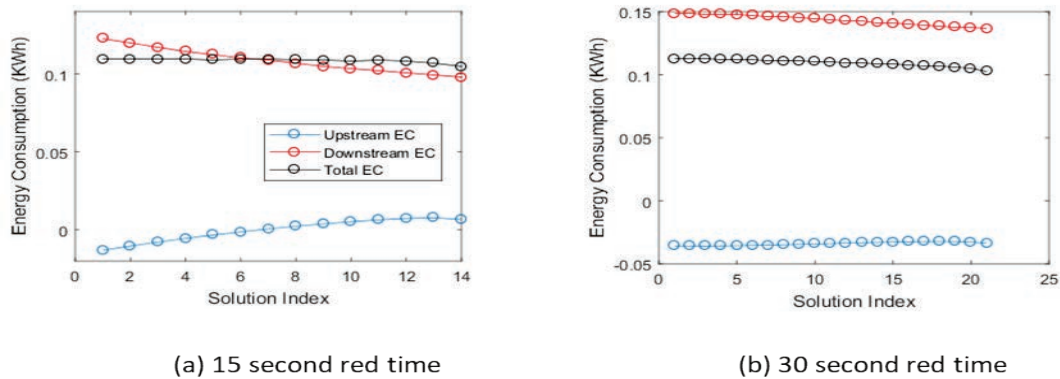


Figure VII.3.4 BEV Eco-CACC-I results at 40 mph

Finally for Task 4, the team developed an eco-predictive control system for BEVs that integrates a BEV energy consumption model and vehicle powertrain model to save fuel while maintaining the vehicle speed within a user-specified speed range. The developed control will be used as the lead vehicle controller in the Eco-CACC-U controller. The study tested the eco-predictive control on an 18 km section of I-81 and found that the proposed system saved 6.12% and 11.16% of energy on uphill road and downhill road sections, respectively. This study demonstrated that regenerative energy in BEVs is a critical factor in energy efficiency and the proposed eco-predictive control significantly improved the energy efficiency for BEVs using a given road topography in a predictive manner. Figure VII.3.5 shows the sample result of the proposed eco-predictive control system. Additionally, a proportional derivative platooning algorithm of the proposed Eco-CACC-U system was developed to deal with multi-vehicle platoons. The proposed control approach uses information from both the immediate predecessor and the platoon's leader to update the speeds of the different following vehicles within the platoon. Even though that results in a more complex controller, making the followers cooperative with the first vehicle in the platoon is deemed essential in order to ensure the overall stability and efficiency of the Eco-CACC-U system.

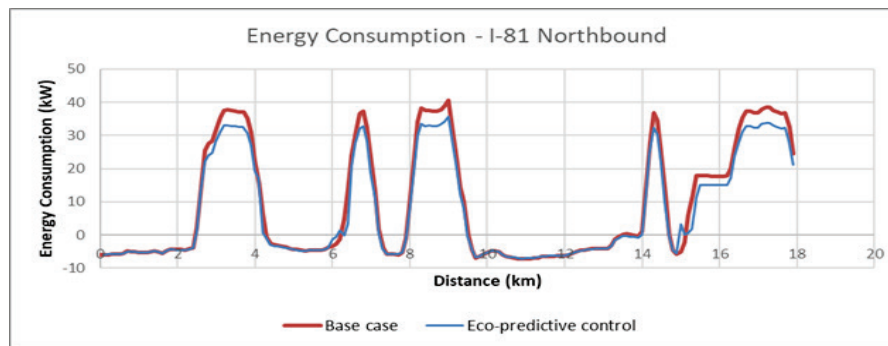


Figure VII.3.5 Energy consumption of the eco-predictive control on Interstate-81

Conclusions

This project develops a novel Eco-CAC system that integrates VD control with CAV applications. The project includes eight primary tasks and their associated sub-tasks. The research team is currently working on tasks 1 through 4. The tasks include (1) eco-routing system development, (2) strategic control algorithm development, (3) Eco-CACC-I algorithm development, and (4) Eco-CACC-U algorithm development. Currently, the team is developing (1) a new simple power-based microscopic HEV fuel consumption model that can be implemented in various CV and eco-driving applications, (2) the eco-routing algorithm for BEVs, (3) the NFD and gating algorithm to reduce network congestion, (4) a preliminary BEV Eco-CACC-I controller for a single signalized

intersection, (5) the acceleration and deceleration control strategies for the Eco-CACC-U controller, and (6) a predictive eco-driving control system for BEVs that generates an optimal speed control using roadway grade information.

Key Publications

1. Chen H. and Rakha H.A., "Developing a Traffic Signal Eco-Cooperative Adaptive Cruise Control System for Battery Electric Vehicles," Submitted to the Transportation Research Board (TRB) 98th Annual Meeting, Washington DC, January 13-17, 2019.
2. Elbery A. and Rakha H.A., "City-wide Modeling of Mobility and Communication System Interactions: An Eco-routing Case Study," Submitted to the Transportation Research Board (TRB) 98th Annual Meeting, Washington DC, January 2019.
3. Ahn K. and Rakha H.A., "A Simple Hybrid Electric Vehicle Fuel Consumption Model Based on Instantaneous Vehicle Speed and Power Levels," Submitted to the Transportation Research Board (TRB) 98th Annual Meeting, Washington DC, January 2019.
4. Du J. and Rakha H.A., "Constructing a Network Fundamental Diagram: A Synthetic Origin-Destination Approach," Submitted to the Transportation Research Board (TRB) 98th Annual Meeting, Washington DC, January 2019.

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VII.4 Evaluating Energy Efficiency Opportunities from Connected and Automated Vehicle Deployments Coupled with Shared Mobility in California (UCR/NREL)

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Start Date: October 1, 2017	End Date: September 30, 2019	
Project Funding (FY18): \$407,000	DOE share: \$297,000	Non-DOE share: \$110,000

Project Introduction

With the rapid growth of information and communication technologies, Connected and Automated Vehicles (CAVs) are deemed to be disruptive with the potential to significantly improve overall transportation system efficiency, however may increase (vehicle miles traveled) VMT. Further, shared mobility systems are another disruptive force that is reshaping our travel patterns, with the potential to reduce VMT. The goal of this project is to extensively collect data from vehicles and associated infrastructure equipped with CAV technologies from both real-world experiments and simulation studies mainly deployed in California, and develop a comprehensive framework for evaluating energy efficiency opportunities from large-scale (e.g., statewide) introduction of CAVs and wide deployment of shared mobility systems under a variety of scenarios.

Objectives

As a complement to existing studies on nationwide evaluation of CAVs' energy impacts, this project is focusing on data collection efforts and CAV applications under congested traffic environments that are frequently experienced on a massive scale across the major metropolitan areas in California. Another key component of this project is to consider the interaction between different CAV technologies and the compound effect on energy efficiency. The outcomes from this project are expected to help close the knowledge gap on recognizing the potential energy impacts of a broad (regional or statewide) deployment of CAV technologies across a wide range of roadway infrastructure with varying levels of congestion and different penetration of shared mobility systems. In addition, the results from this project will support policymakers in steering CAV development and deployment, coupled with shared vehicle systems, in an energy favorable direction. To realize these outcomes, the specific objectives of this project are:

- To collect data from both real-world implementations (including experiments, demonstrations, and early deployments) and simulation studies of CAV technologies, potentially coupled with shared mobility, mainly in California. The real-world data will be used to model the energy efficiency from each individual CAV technology with a small fleet of equipped vehicles, while simulation data will facilitate the analysis of aggregated effects on traffic with multiple CAV technologies concurrently deployed.
- To implement models for quantifying the impacts of CAV technologies on energy intensity (e.g., energy consumption per unit distance for different driving conditions) and for quantifying the amount of driving (measured by vehicle miles traveled or VMT) represented by each driving condition. The models will include the consideration of vehicle class, roadway type, level of traffic, and level of vehicle automation.

- To construct a regional or statewide energy inventory under various CAV technology deployment scenarios by incorporating datasets and models for predicting vehicle market share and vehicle usage, which are tightly associated with the penetration of shared mobility systems, including transportation network companies (TNCs), ride-sharing, carsharing, ride sourcing, etc.

Approach

This research project has been divided into three phases:

Phase I – Data collection and processing (complete)

The data collected from existing CAV and shared mobility applications is the foundation of model implementation and energy efficiency evaluation. For the CAV-impacted traffic, the energy intensity profiles have to be recalibrated in term of the penetration of CAVs. Shared mobility applications, especially those are coupled with CAV technologies (e.g. autonomous taxis), remarkably change the traffic demand and VMT of the current transportation system. Both CAV and shared mobility models need a large amount of real world and simulation data to estimate the impact of the new mobility solutions.

During this phase, the real-world data were collected from multiple sources, e.g. on-road test vehicle and testbed, Dynamometer-in-the-Loop (DIL) platform, and published data from existing experiments. Below is a selection of the experiments the research group have conducted to collect new data.

Connected Eco-driving at Riverside Innovative District:

New field experiments were conducted along the University Avenue corridor between UC Riverside and downtown Riverside, CA. As a key part of the Riverside Innovative Corridor, broadcasting-enabled signal controllers along with DSRC roadside units have been deployed at each main intersection. A research test vehicle has been set up for the field test. It is equipped with a Dedicated Short-Range Communication (DSRC) onboard unit and a real-time automotive radar system. The on-board system receives position information via GPS, and vehicle dynamics information through on-board diagnostics (OBD). The GPS traces, Signal Phase and Time (SPaT) information and vehicle dynamic states from on-board diagnostics devices were archived during the test.

Dynamometer-in-the-Loop (DIL) test for Connected Eco-bus:

We have collected partial automated heavy-duty CAV data under the ARPA-E NextCAR Connected Eco-bus project, in which part of the DIL test will be performed by the vehicle controller. In this test, a high-fidelity traffic simulator provides inputs to both the vehicle longitudinal and powertrain control modules, as well as the dynamometer controls. There are four major blocks in the system: microscopic traffic simulation tool, vehicle dynamics optimization, powertrain control optimization and a plug-in hybrid electric vehicle (PHEB) on Heavy-Duty Chassis Dynamometer (HDCD). This DIL platform provides an ideal virtual reality environment to support comprehensive evaluation of the Connected Eco-PHEB Prototype under a variety of testing scenarios.

Truck Eco-Drive around Port of LA:

In Eco-FRATIS project, 20 trucks are being deployed with connected eco-driving system to traverse connected intersections under eco-speed advisory. Fifteen intersections from LA County near the port are being equipped with SPaT-broadcasting enabled controllers and 4G routers for communication. The Truck Eco-Drive system has multiple innovative features which are adaptive to the large-scale deployment of connected vehicles, such as 4G network-based communication, tablet-based onboard system, and Mobileye-based preceding vehicle warning system.

Vehicle trajectory output from advanced traffic simulation models is another key source of CAV data. The research team have developed and implemented multiple CAV applications, such as EAD, Eco-Cooperative Adaptive Cruise Control, eco-speed harmonization, in the traffic simulators Paramics and VISSIM. The simulation datasets provide a substantial supplement to the field data in evaluating the energy efficiency

impact of CAV applications. The research team have also collected more simulation data from ongoing projects, such as the data Cooperative Adaptive Cruise Control (CACC)-enabled Eco-Approach and Departure (EAD) in VISSIM, and CAV Applications Effectiveness Analysis in VISSIM. In parallel with the field data collection from Connected Eco-bus and Truck Eco-Drive project, the same road network is also coded in VISSIM to cross-validate the real-world performance of CAV applications.

Phase II – Model Implementation (ongoing)

The system architecture and methodology in the model implementation phase is summarized in Figure VII.4.1.

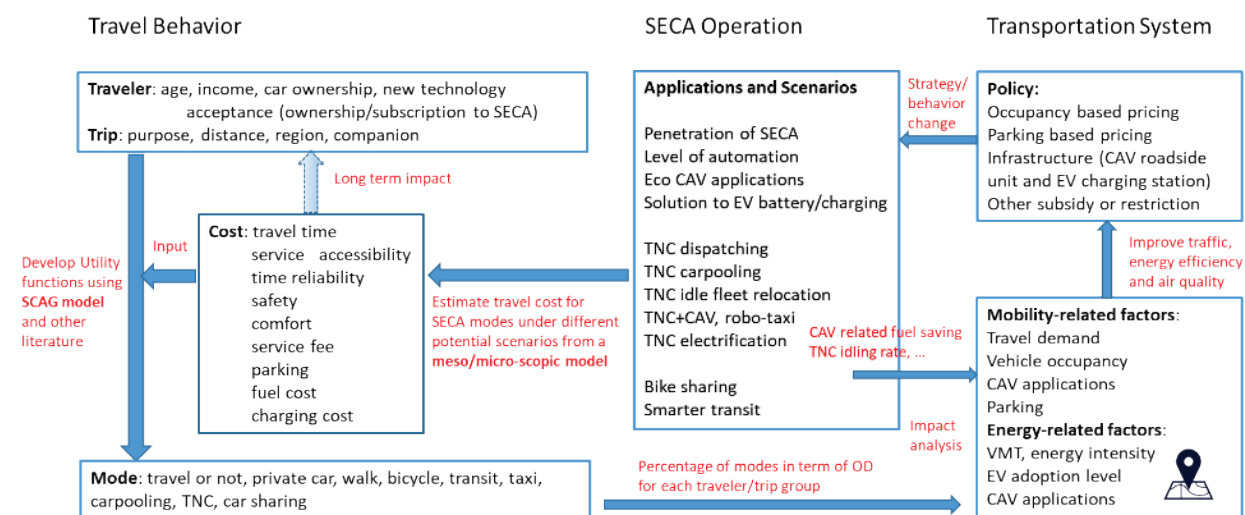


Figure VII.4.1 Model Framework

In the proposed framework, there are three levels and six key components, as shown in Figure VII.4.1.

The travel behavior level shows how travelers evaluate different travel cost factors and choose the travel mode, including: 1) **travelers and trips**: Demographic information and trip purposes distribution provided by census data and regional transportation planning model (e.g. SCAG model); 2) **travel cost**: The average value of travel cost attributes (e.g. travel time, service accessibility, fuel/charging cost, etc.) for specific origin-destination (OD) under certain scenarios; and 3) **travel mode**: The decision to make a trip or not, and the mode options the traveler may take. This decision process can be informed by data collected through the DOE SMART Mobility WholeTraveler project.

To develop the behavior model, the research team reviewed the literature related to mode choice modeling in order to evaluate the impacts of CAVs and shared mobility on travelers' mode choice decisions. Based on literature review, tour-based mode choice modeling framework was selected for model development, given its advantage of realistically representing the constraints of time and space, and the linkages among activities. Among methodologies that were commonly used for mode choice modeling, the nested logit model does not suffer from the limitations caused by the Independence of Irrelevant Alternatives property and has the flexibility of combining the stated preference and revealed preference data. Therefore, the nested logit model is chosen for later modeling process.

The Shared Electric Connected and Automated (SECA) operation level shows future traffic scenarios (in terms of market penetration, automation level, etc.) and the corresponding operation performance. We identify future transportation system scenarios in terms of different SECA penetration and development levels and employ a mesoscopic simulation platform to accommodate all major SECA applications. The real-world data and micro-simulation data collected from CAV applications are used to calibrate the parameters in the platform, e.g. link capacity and energy efficiency. Findings from the DOE SMART Mobility and

WholeTraveler project will assist in identifying likely SECA penetration levels in future scenarios at a population scale.

As the key component of the model framework, the mesoscopic platform is the playground where all operations of CAV and shared mobility are simulated and analyzed with varying application and scenarios. After comparison with other mesoscopic agent-based traffic simulator (e.g. MATSIM, Polaris), the research team selected BEAM as the main simulation platform due to its support to TNC modeling, effectiveness on large-scale network and possible synergy with its previous and ongoing work in California.

At the **transportation system level**, impact analysis is conducted on mobility and energy-efficiency. The factors that affect the performance of the transportation system, such as travel demand, vehicle occupancy and adoption of CAV applications are integrated to analyze the impact of the new technologies on mobility, e.g. congestion level, VMT change and speed distribution. The VMT and speed bin information are then applied to the energy-intensity model which is calibrated from a large set of real-world drive cycles simulated in FASTSim. In this way, we evaluate the state-level energy-intensity impact of CAV technology coupled with shared mobility. We then review and evaluate the policies, e.g. occupancy or parking-based pricing, to mitigate the potentially increased traffic congestion and energy consumption due to the induced travel demand and VMT.

Phase III – Energy Impact Evaluation (starting soon)

Based on the model framework developed in Figure VII.4.1, a California regional or statewide energy inventory will be constructed from the integration of CAV-induced impact factors with relevant datasets and models to evaluate the energy efficiency opportunities from CAV deployment coupled with shared mobility in California. Sensitivity analysis on some key factors (e.g., penetration rate, automation level) will also be conducted.

Results

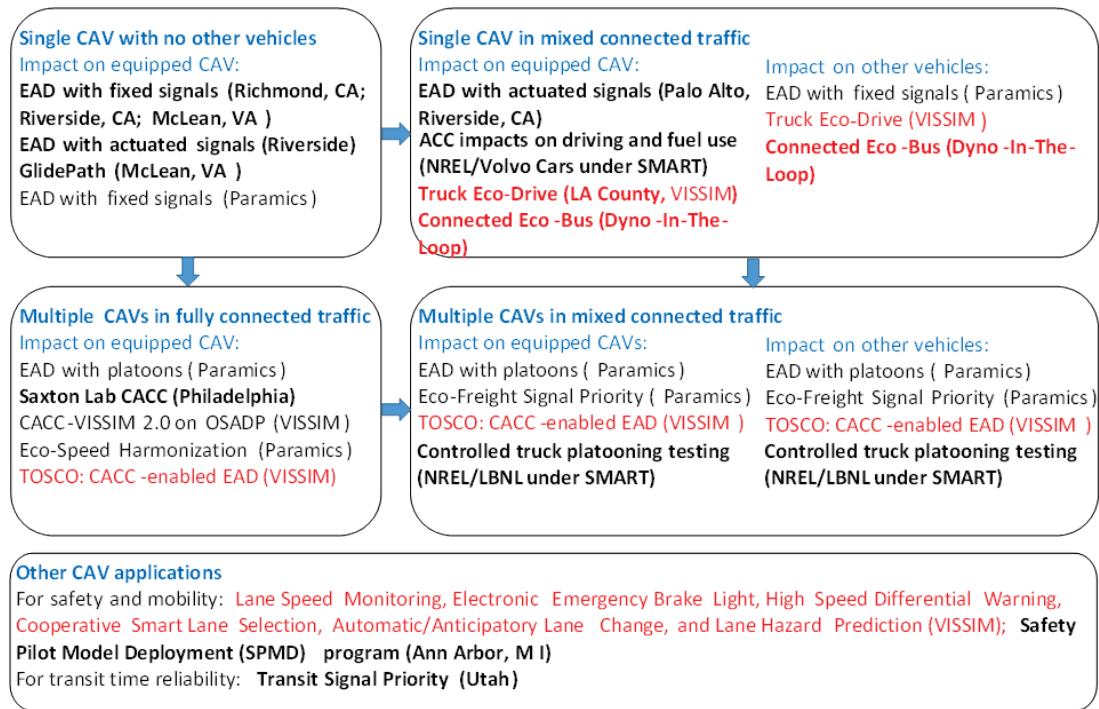


Figure VII.4.2 Datasets and major scenarios of CAV applications and experiments

By the end of the first year, the research team has completed the data collection task in Phase I. Real-world and simulation data from light-duty vehicles (LDVs), heavy-duty vehicles (HDVs), and infrastructure equipped with a set of CAV technologies are identified, collected and processed. The datasets we have collected are summarized in Figure VII.4.2. To collect and process sufficient and diverse data that satisfy the need of a comprehensive impact analysis, we first define five major scenarios that would cover almost all CAV applications and experiments in Figure VII.4.2: 1) Single CAV with no other vehicles; 2) Single CAV in mixed connected traffic; 3) Multiple CAVs in fully connected traffic; 4) Multiple CAVs in mixed connected traffic; and 5) Other CAV applications. This partition would address many CAV-related factors that would impact traffic energy efficiency, including traffic demand, CAV penetration, automation level and vehicle type distribution.

We then group the existing CAV datasets from previous field and simulation experiments into those 5 categories, showing their names using black font color. The real-world experiments are highlighted using bold font. This figure clearly shows that the previous experiments (especially the field test) placed more emphasis on ideal cases with single vehicle and fully connected environment. The scenarios with multiple CAVs and mixed connected traffic need more experiments and data (from both equipped CAVs and other conventional vehicles) to support the CAV impact analysis. Therefore, the data collection phase of this project included designing and implementing new experiments (highlighted in red font color) that are highly focused on multiple (and cooperative) CAVs and mixed connected traffic, which is more realistic in the transportation system of the near future. As shown in the diagram, heavy-duty vehicles, such as buses and trucks, are another emphasis in new datasets collected in this project.

Based on the field experiment and simulation data, we evaluate the performance of different CAV applications under diverse traffic demand, signal type, market penetration rate, etc. As an example, Table VII.4.1 shows a selection of the Eco-Approach and Departure (EAD) field tests in which the UC Riverside team has participated, along with the test location, communication type and performance of each eco-driving application. As shown in the table, the energy saving of the vehicle equipped with EAD system vary from 2.5% to 28% in comparison with the baseline vehicle operated by an uninformed driver.

Table VII.4.1 Connected Vehicles based eco-driving field test

Technology	Location	Communication	Energy Savings	Ref
EAD with Fixed Signals	Richmond, CA	4G/LTE	14%	[1]
	Riverside, CA	DSRC	11%-28%	[2]
	McLean, VA	DSRC	2.5%-18%	[2]
EAD with Actuated Signals	Riverside, CA	DSRC	5-25%	[3]
	Palo Alto, CA	DSRC	7%	[4]
GlidePath (HMI-assisted)	McLean, VA	DSRC	5%	[5]
GlidePath (Automated)	McLean, VA	DSRC	17%	[5]

Although field experiments would better validate the proposed algorithm by the practical results from the real-world traffic, micro-simulation is still necessary in some cases if the designed scenario is difficult to implement in the real world. For example, the CACC-enabled EAD study in VISSIM provide a comprehensive analysis of this technology under different traffic congestion levels and market penetration rates. The study site is along State Highway 105 (SH-105), Conroe, TX, running coordinated actuated signal control (with Econolite ASC3 controllers). There are three lanes in both directions of SH-105, with the speed limit of 55 mph. The simulation model was calibrated against a typical weekday during the morning peak hour. The traffic volumes of SH-105 EB and SH-105 WB are 2045 vehicles per hour (vph) and 1082 vph, respectively. Under

the calibrated traffic congestion level, various scenarios with different market penetration rate (MPR) of equipped vehicles, i.e., 0% (baseline), 20%, 40%, 60%, 80%, and 100%. Table VII.4.2 presents the environmental benefits that equipped vehicles may bring out to the system. The reduction in CO2 emission and energy consumption may vary from 1.4% - 6.5%.

Table VII.4.2 Environmental Impacts of CACC-enabled EAD

Penetration	CO ₂ (g/mile)	CO ₂ (% of reduction)	Energy(kJ/mile)	Energy (% of saving)
Baseline	16.9	-	234.8	-
20%	16.6	1.78	231.6	1.36
40%	16.5	2.37	229.8	2.13
60%	16.4	2.96	227.5	3.11
80%	16.1	4.73	224.2	4.51
100%	15.8	6.51	220.0	6.30

The research team is also working on the model implementation phase, with a focus on the simulation of CAV and shared mobility impacted traffic in BEAM. Figure VII.4.3 shows the simulation network of City of Riverside in BEAM. The population activity is the key input for the model. It defines the travel schedules of all the virtual population in the simulated area, which should be generated by the local agent based microscopic travel demand model. The Southern California Association of Government offers us their SCAG travel demand model which can output aggregated travel demand in a mesoscopic resolution (TAZ level OD pairs). To obtain the agent-based activities from the OD table, an activity generation algorithm is then developed to produce schedule. The census block population distribution data is utilized in this algorithm. With these inputs, the preliminary BEAM simulation environment is built and the BEAM model is ready to work. The next scope of work is to analyze the output of the simulation and calibrate the model in terms of CAV and share mobility scenarios.

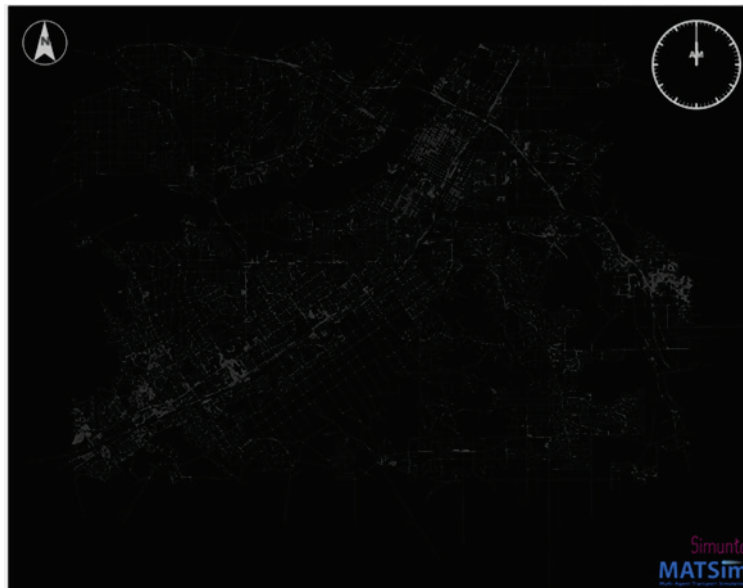


Figure VII.4.3 Simulation network of City of Riverside in BEAM

Conclusions

In this project, extensive real-world data collection supplemented with simulation studies to cover a variety of scenarios, including different vehicle types and fuel/powertrain technologies, combination of CAV applications, various levels of automation, roadway characteristics, and traffic conditions. The outcomes from this project are expected to help close the knowledge gap on recognizing the potential performance and energy impacts of a broad deployment of CAV technologies across a wide range of roadway infrastructure with varying levels of congestion. This will: 1) support policymakers in steering CAV development and deployment in an energy favorable direction; 2) increase the confidence of CAV technology investors both on the infrastructure side (i.e., transportation agencies) and on the vehicle side (i.e., OEMs); and 3) expedite the deployment of promising CAV and shared mobility applications.

Key Publications

1. At this point in the project, there are no publications to report. We are working on a paper regarding the data collection effort and BEAM modeling.

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1. H. Xia, K. Boriboonsomsin, F. Schweizer, A. Winckler, K. Zhou, W.B. Zhang, M. Barth, "Field Operational Testing of ECO-Approach Technology at a Fixed-Time Signalized Intersection", Proceedings of the IEEE 2012 Intelligent Transportation Systems Conference, Anchorage, AK, September 2012, 6 pp.
2. H. Xia, "Eco-Approach and Departure Techniques for Connected Vehicles at Signalized Traffic Intersections". Doctoral dissertation, University of California, Riverside, 2014.
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4. P. Hao, G. Wu, K. Boriboonsomsin, M. Barth. "Preliminary Evaluation of Field Testing on Eco-Approach and Departure (EAD) Application for Actuated Signals", ICCVE 2015, Shenzhen, China. Oct. 2015.
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VIII Core Modeling, Simulation, and Evaluation

VIII.1 Vehicle Systems and Mobility Research (ANL)

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Start Date: October 1, 2017

End Date: September 30, 2018

Project Funding (FY18): \$1,000,000

DOE share: \$1,000,000

Non-DOE share: \$0

Project Introduction

This work utilizes a mix of novel on-road, on-track, and in-laboratory experimentation supplemented with targeted prototype system experiments and long-term in-field data collection and seeks to support DOE's EEMS work by adding to the state-of-knowledge, in-filling highlighted data gaps, and providing experimental results and justifications for promising eco-Connected and Automated Vehicle (CAV) technology and operational concepts.

Objectives

- Investigation of vehicle-following aerodynamic impacts related to following distance and speed for 2 light-duty vehicles through application of novel direct tractive force measurement and refined experimental procedures.
- Collection and analysis of real-world behavior and utilization for a range of production Adaptive Cruise Control (ACC) systems
- Integration of CAV capabilities in the dynamometer laboratory environment for robustly evaluating current and emerging CAV concepts and supporting researchers through Hardware/Software/Vehicle-in-the-loop capabilities and data collection.
- Investigation of expanded sensing and awareness capabilities of emerging CAV technologies and how to leverage these "vehicle-as-a-sensor" concepts for improved efficiency and mobility.

Approach

Vehicle Following Aerodynamic Impacts

Building on previous Argonne developed instrumentation and experimental capabilities, this work sought to directly measure the aerodynamic load improvements associated with vehicle following for a range of speeds and following distances. To this end, track testing as described in the figure below was performed at several speeds and following distances (including a control “alone” reference point). Direct axle torque measurements were used to measure the road load forces associated with a particular gap/speed configuration allowing for a direct estimate of aerodynamic road load force reduction. This is in contrast to other methods that investigate pressure differentials or fuel rate differences across the range of desired speed and gap configurations.

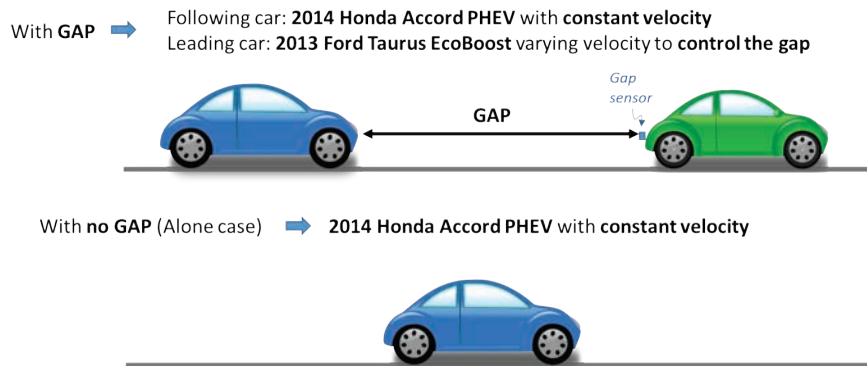


Figure VIII.1.1 Experimental Setup for 2-Vehicle Aerodynamic Following Impacts Assessment

On-Road Data Collection and Analysis of Adaptive Cruise Control Equipped Vehicles

In order to better understand the real-world behaviors and outcomes of Adaptive Cruise Control operation (as a starting point for more complex CAV behaviors), a range of commercial ACC equipped vehicles were evaluated under a mix of real-world routes and conditions with and without the ACC system active. As described in the figure below, a mix of driving styles (routes) as well as vehicle and powertrain types were assessed providing real-world usage and benefits related to ACC operation.

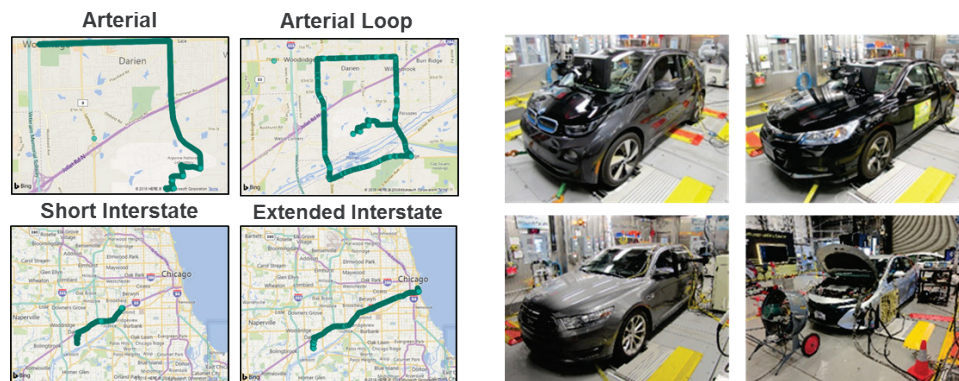


Figure VIII.1.2 Highlighted On-Road Driving Routes (left) and On-Road Experimental Vehicles (right)
[clockwise from upper-left – BMW i3 ReX, Honda Accord PHEV, Toyota Prius PRIME PHEV, Ford Taurus IC vehicle]

CAV Laboratory Development and Experimentation

While the concept of a CAV laboratory can be relatively far reaching, this year’s focus was on emulating the vehicle-centric aspects of a CAV operating environment in a laboratory setting. More specifically: 1)

emulating the “driver” of a vehicle in an automated situation either via a robotic driver, man-in-the-middle CAN override, or human driver following a modified drive-trace and 2) modifying the traction environment emulated by the dynamometer (tractive force at a given speed/”location”/operational-situation) to be more representative of the true on-road tractive loads (i.e. close following aero. impacts or grade).

Vehicle-as-a-Sensor Examination

In parallel to the On-road Data Collection task mentioned above, the on-road data is also used to inform this effort seeking to investigate additional and alternative uses for the new streams of data and information coming from Connected and Automated Vehicles. By leveraging a vehicle’s collision avoidance sensors, ACC system, and GPS location, promising research possibilities begin to open up regarding extracting new information about roadway, traffic and other related conditions. To better illustrate the type of data collected in this preliminary investigation, the figure below highlights the radar and imaging data for a single location and point in time from the vehicle-as-a-sensor platform used during data collection.

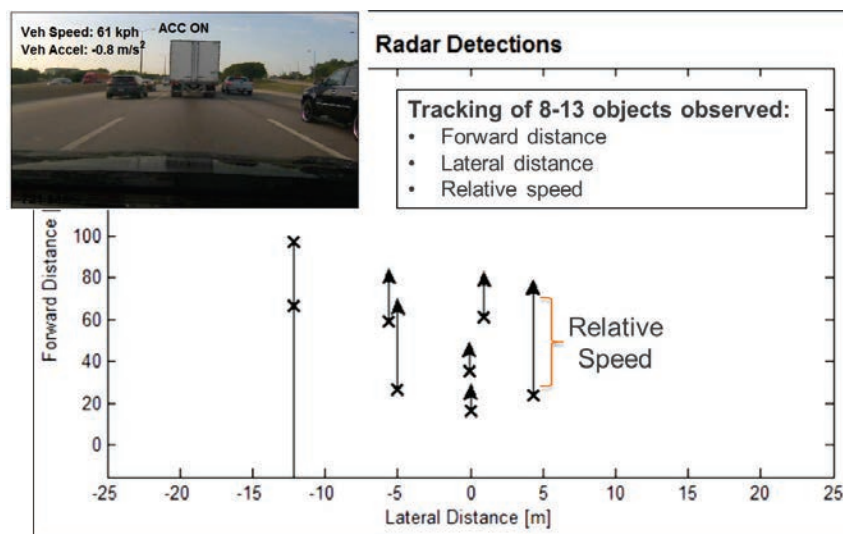


Figure VIII.1.3 Highlighted Radar and Video Images from Vehicle-as-a-Sensor Preliminary Data Collection

Results

The following sections provide some highlighted conclusions from the tasks describe above. Many additional data, analysis and conclusions have arisen from this work and are out of the scope for this abbreviated overview.

Vehicle Following Aerodynamic Impacts

The plot below summarizes the results from the two-vehicle following aerodynamic impact study for a range of following time-gaps and two speeds. From the figure below, it can be seen that aerodynamic benefits increase significantly as the gap between vehicles decreases to roughly 0.4-0.5s, but closer following appears to actually provide slightly diminished benefits. These findings are in line with other previous vehicle following research and suggest that intelligent vehicle following may be beneficial versus a constant push for the closest possible following distance/time gap. Additionally, overlaying approximate bands for various automated following technologies (CACC, ACC, etc.) indicates that additional technical improvements beyond recent CACC vehicles will be necessary to achieve the expected benefits seen in very close following.

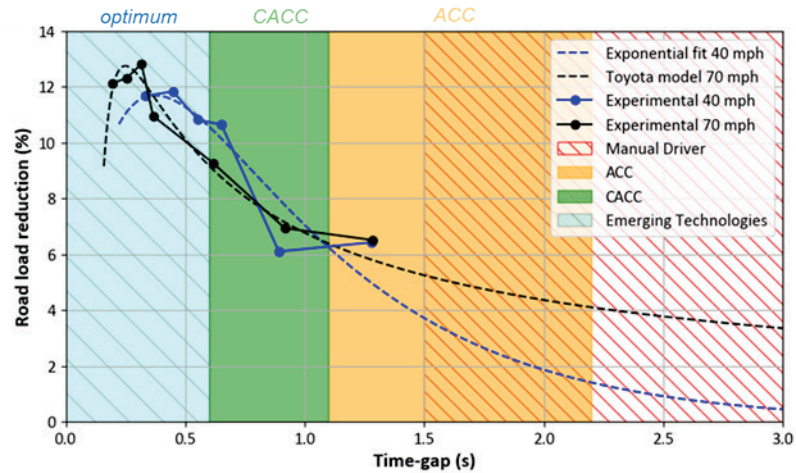


Figure VIII.1.4 Highlighted Road-Load Force Reduction for Varying Vehicle Time Gaps and Speeds for 2-Vehicle Experiments

On-Road Data Collection and Analysis of Adaptive Cruise Control Equipped Vehicles

As discussed above, a range of ACC vehicles were operated under real-world driving conditions over a series of prescribed driving locations to provide a mix of usage while retaining some degree of consistency in terms of day-to-day variations. This information was used for a variety of insights related to this initial step into the future of vehicle automation. For example, by aggregating ACC operating points from in-field, one can begin to see operational differences between different ACC implementations. The figure below highlights the observed ACC operational envelope for two vehicles. It is clear from the observed usage data that the Prius Prime (left) has the capability of low-speed ACC operation as well an expanded envelope of acceleration capabilities. This data and analysis provides evidence that ACC systems themselves differ in terms of their implementation, utilization, and capabilities, thus their expected in-field impacts related to fuel consumption, traffic flow, and many other items will likely differ and necessitate in-field data collection and experimentation.

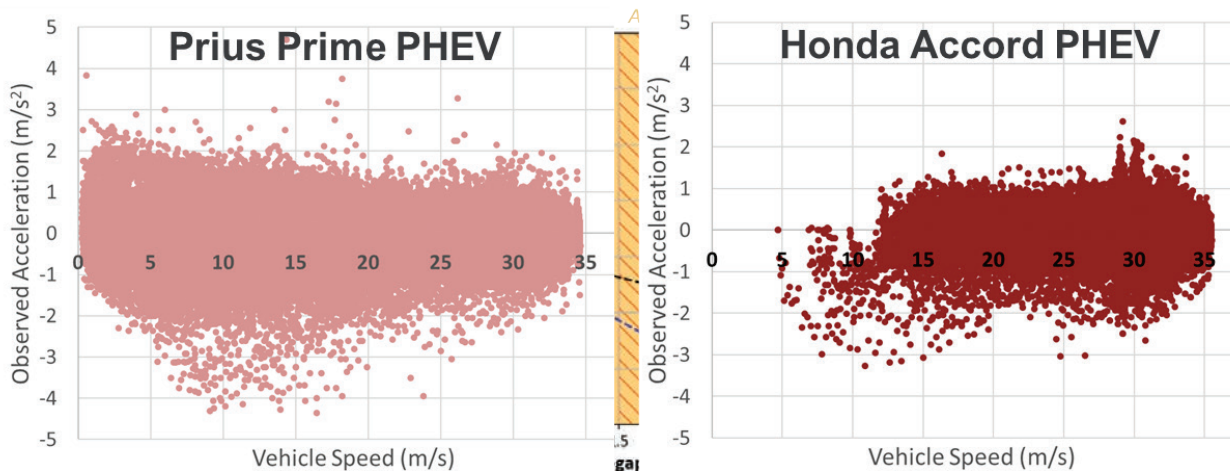


Figure VIII.1.5 Observed ACC Operational Envelopes for Two Select Study Vehicles

Relatedly, this information can be used to characterize an ACC system’s behavior such that a vehicle’s ACC strategy can be used to establish modified drive cycles to evaluate the impact of a particular smoothing/following strategy.

CAV Laboratory Development and Experimentation

While many refinements were added to Argonne’s laboratory, instrumentation and experimental capabilities within this fiscal year, two highlights include: 1) upgraded robotic driver capable of handling CAV type behaviors and 2) Man-in-the-Middle CAN override capabilities used to operate a production ACC system within a laboratory environment.

As summarized in the figure below, the laboratory’s robotic driver was modified for a range of CAV relevant input/outputs and used for two specific, high-impact use cases. More specifically, the system was adapted to provide highly repeatable acceleration and deceleration trajectories used in a range of eco-launch/stop studies. The increased reliability and repeatedly provided by the robot versus a human driver is imperative for examining a range of possible strategies with sufficient statistical robustness. Secondly, the driver was also modified to provide an ACC “driver” for vehicles not equipped with ACC. This was particularly useful since experiments regarding a particular ACC strategy could be consistently applied over a range of vehicles without requiring that the experimental vehicles have a stock ACC system. Looking forward, these modifications will be a key part of the future of automated vehicle laboratory testing in support of DOE’s EEMS and SMART efforts.

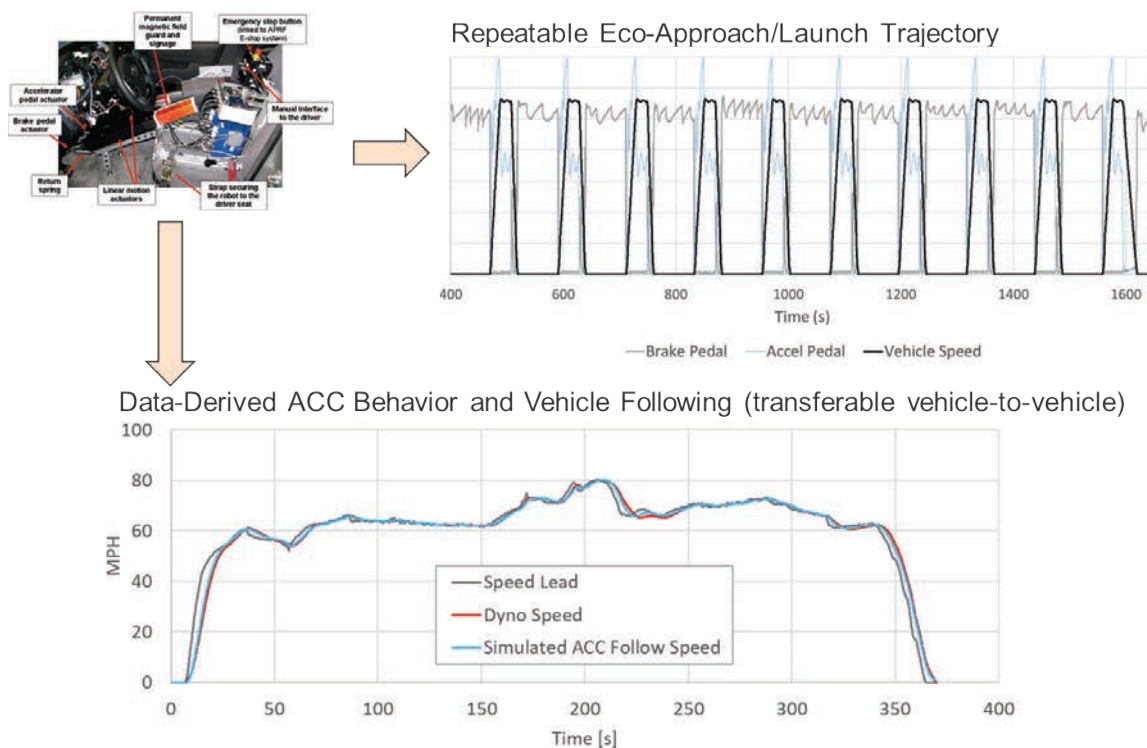


Figure VIII.1.6 Highlighted Robotic Driver Use Modifications and Use Cases

In addition to the robotic driver capabilities, a man-in-the-middle (MiM) CAN override approach was also demonstrated for a Prius Prime research vehicle. This override allowed a lead vehicle to be emulated within a following vehicle’s ACC system, thus allowing the vehicle’s true behavior to be replicated in a dynamometer laboratory environment. This has a variety of beneficial impacts, including more repeatability, more experimental control, the ability to push the vehicle into atypical scenarios as well as other benefits associated with laboratory testing over on-road data collection. One of the most interesting and powerful capabilities of this MiM technique is that specific control parameters (such as following gap time target versus vehicle speed as shown below) as well as specific maneuvers can be explicitly probed in a controllable and high-fidelity laboratory environment. The data below was generated by emulating a steady-state vehicle ahead of the test

subject and observing the emulated gap distance (and thus time) at which the following vehicle’s speed stabilized around the targeted speed.

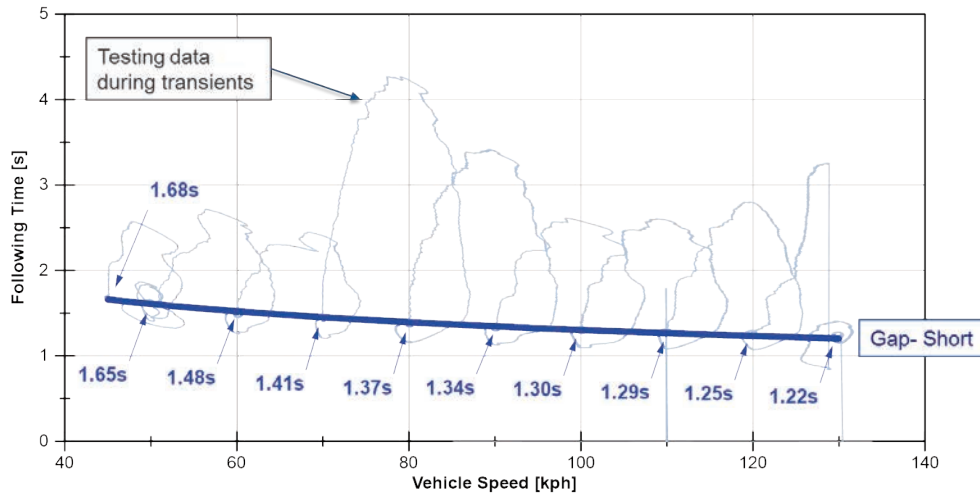


Figure VIII.1.7 Prius Prime ACC Target Following Time versus Vehicle Speed

As mentioned above, another use for the CAN MiM override is that production ACC systems can be operated in a laboratory environment (thus affording the benefits of a laboratory while retaining the new CAV operational functionality). Shown below is driving data from the US06 cycle with the ACC system active (and running with the MiM active) as well as from a conventional “manually” driven drive cycle. Smoothing due to the ACC system can be observed in contrast to the nearly overlaid match between lead and following vehicle for the manually driven case. While the ACC results themselves are relevant, this also proves the concept that CAV functionality can be incorporated in the laboratory, laying the groundwork for continued research and development related to operating a range of CAV behaviors and technologies in a laboratory environment.

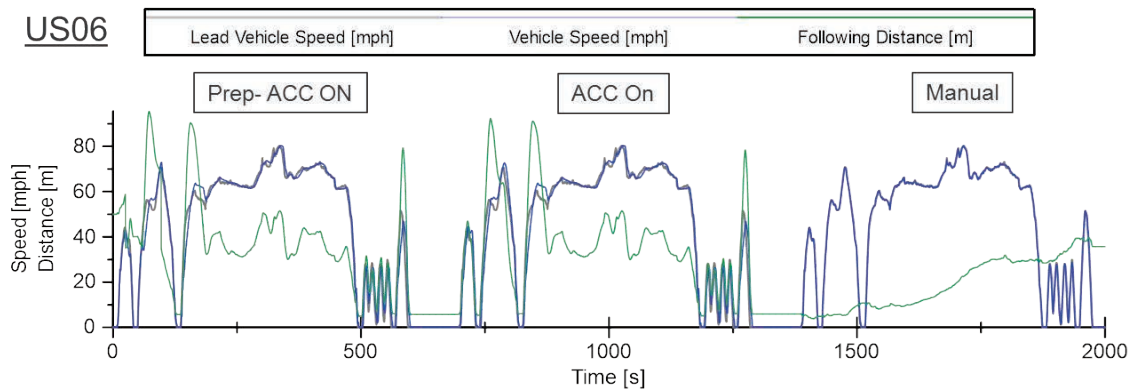


Figure VIII.1.8 Laboratory Experiment Driving US06 with ACC MiM Active and Emulating a Lead Vehicle Following Prescribed Drive Trace

Vehicle-as-a-Sensor Examination

The figure below highlights one important aspect of a vehicle-as-sensor concept. Showing the reported instantaneous gap distance reported by the vehicles ACC system overlaid with the vehicle speed, one can quickly see that the system provides information regarding the traffic dynamics that include the slowing of vehicles as gaps decrease. Even with a single vehicle, this information provides a robust (minimal large step

changes or unrealistic readings) estimate of basic roadway information. In fact, more advanced processing of the ACC system's radar outputs allows a single vehicle to sense multiple gaps within its line of (radar) sight. This reinforces the concept that the additional sensing afforded by CAVs vehicle needs combined with GPS location information will open up many new possibilities for improved real-time sensing and predictions related to roadway conditions and beyond.

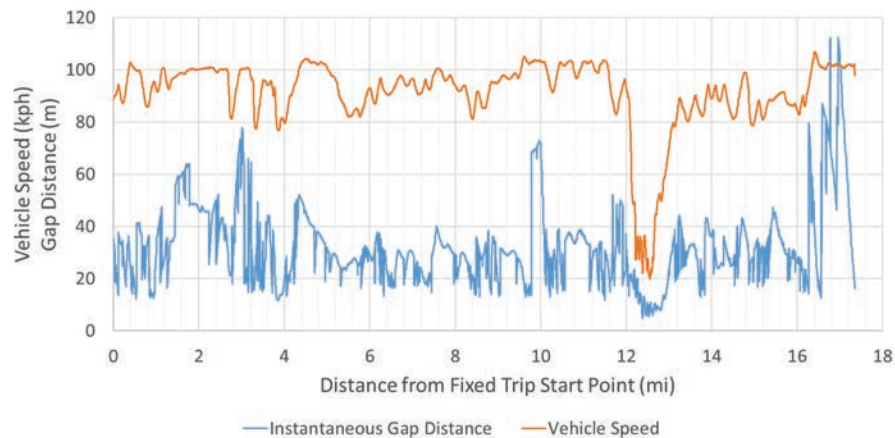


Figure VIII.1.9 Example Vehicle Speed and Sensed Gap Distances for Single Highway Run (from Argonne to Downtown Chicago)

Conclusions

A wide range of CAV-relevant results, analysis and data have been developed by these efforts. More specifically, this work has provided:

- Improved estimates of vehicle aerodynamics at a range of following distances and speeds while developing and refining novel methods for direct tractive load assessment.
- On-road data collection for a range of current ACC equipped vehicles providing critical information regarding the current state-of-the-art as well as providing a foundation onto which new CAV behaviors and analysis can be incorporated.
- Laboratory adaptations to evolve dynamometer laboratory testing into a suite of capabilities and methods that can handle the wider needs of CAV behavior emulation while retaining the robustness, safety, and repeatability benefits associated with laboratory testing.
- Information and sensing required by CAVs for automated driving has many additional possibilities for usage that can further inform decisions to improve the efficiency and productivity associated with a given transportation system. Preliminary results are promising in that expected and stable behaviors appear, thus continued research into how a vehicle itself can become a sensor within the wider transportation environment is of continued research interest.

Key Publications

1. "On-Track Measurement of Road Load Changes in Two Close-Following Vehicles: Methods and Results", SAE World Congress (under review), 4/9/2019

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Acknowledgements

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VIII.2 Core Modeling: Maintenance; Tools; Real World Energy Impact Estimation; and Toyota Prius Prime Validation (ANL)

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VIII.2.1 Maintenance

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

- Allow VTO to use similar tools as OEMs to get consistent results related to state-of-the-art software for energy consumption, performance, cost and mobility analysis
- Support large user community (>250 companies worldwide) including OEMs, National Laboratories, suppliers...
- Upgrade AMBER, Autonomie, RoadRunner, SVTrip and POLARIS to continue to work with the latest releases of third party tools (e.g., Matlab/Simulink, Microsoft .NET)
- Integrate models, data, use cases funded by DOE
- Support any unplanned specific DOE request, including component technology, requirements, analysis

Results

Over 800 support requests from OEMs, suppliers, universities and national laboratories were answered this year showing the level of interest in Autonomie. During this fiscal year, three releases of Autonomie were made: REV16, REV16SP1 and REV16SP2.

REV16 included thirteen new Medium and Heavy Duty vehicles, which included ISG, PHEV, and BEV variants for transit bus. It also includes the Prius Prime and the 2nd generation Voltec. There were also new multimode and hybrid DCT powertrains. A generic thermal configuration along with a new configuration supporting 48-volt systems was also included in this release. All of these configurations were developed to support studies.

The REV16SP1 release was based on REV16 just with several bug fixes and enhancements. These were provided by OEMs. The two main issues were handling and building models with a very large number of signals and allowing the solver options to be parameterized. Linux support on clusters was also verified and several distributed computing issues dealing with the new project options and propagating the project options to the workers were resolved in the Matlab backend. These were critical in supporting our OEM users.

Finally, in the fourth quarter, there was the REV16SP2 release, which had several minor updates to the Autonomie dictionary, which is shared with AMBER. The default libraries and repositories were also reorganized and repackaged in a way more compatible with AMBER.

VIII.2.2 Core Modeling Tools

Project Introduction

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.

Objectives

- Support a much larger number of MBSE workflows within the user interface
- Develop a new system integration platform that support Smart Mobility activities
- Develop new workflows that support Smart Mobility activities

Results

AMBER has succeeded in creating a flexible platform on which DOE can build its research tools. As shown in Figure VIII.2.2.1, the intent is to build a tool that encompasses the full suite of energy for transportation simulation tools. This will allow DOE to provide answers to some of the most relevant questions about intelligent transportation affecting our nation's energy consumption.



Figure VIII.2.2.1 The Energy for Transportation Workflow

Early in the year, there was an AMBER 1.0 Public Beta release to gather OEM feedback. We received and incorporated their feedback into the tool. Some of the requested improvements include single click-- cycle, model, and configuration import and several speed improvements in loading and viewing thousands of signals in AMBER. In addition, an equivalent of moveable steps in Autonomie was created so that OEMs could customize the default AMBER workflows. As part of this work, our team demonstrated moving an OEM vehicle from legacy Autonomie and running them in AMBER.

At the end of the fourth quarter, there was an AMBER 1.0 release. It is now being phased in for use on DOE studies. As part of the 1.0 release, there were many improvements in AMBER that affect every workflow. Many of the existing Autonomie workflows were enhanced with new user interfaces or improvements. These included the project and user settings, which is a user interface to setup libraries, import settings and other user options. A simulation options user interface was developed to configure the solver. The data analysis workflow was heavily revised to improve significantly the speed of loading results. The vehicle editor also had many bug fixes and performance enhancements.

Regression tests on Jenkins were developed and several tasks were accomplished regarding obfuscation, licensing and deployment. All of these tasks were necessary for deploying a high quality product and allowing seamless updates to the tool. With unit tests and an update process a continuous deployment of patches can be achieved in the future.

Many of procedures were ported from Legacy Autonomie into AMBER. These included gradeability, passing and many certification procedures such as Two Cycle US, Five Cycle, J1711 PHEV, Japan PHEV, EU PHEV, several heavy-duty procedures along with others.

A Matlab backend was also developed to support the integration of optimization routines. This framework can be leveraged in developing optimization workflows in future development tasks.

There were significant improvements to the POLARIS AMBER user interface and the entire POLARIS-GL code based was packaged and added as an action in AMBER. This action is modular and can be reused across workflows such as in the Smart Mobility workflow or the POLARIS workflow.

There were also significant improvements to the Smart Mobility (Energy for Transportation) Workflow, which was updated to incorporate Aimsun, VISSIM and MOVES. The user can now choose between SVTrip and VISSIM for trip generation or choose between Autonomie or MOVES for energy calculations.

VIII.2.3 Real-World Energy Impact Estimation

Project Introduction

Several studies have been done using simulation tools to evaluate the impact of vehicle technologies under real world conditions. All these were done using models that were verified with test data from dynamometers. As part of the other projects sponsored by DOE, University of Michigan has collected a large amount of data from instrumented vehicles under real world driving conditions. This projects utilizes that data to verify the accuracy of simulation models. This effort helps to define levels of confidence in the simulation results involving real world driving conditions.

Past studies have shown that if a vehicle model is built using sufficient data collected from dynamometer tests, the model can be used to predict fuel economy accurately [1], [2]. However many times, modelers are faced with the challenge of building vehicle models using standard library components, and scaling them to the power rating needed in a vehicle. In this case too, the real world cycles were recorded from over 200 different makes and models of vehicles, and building validated models for each of those vehicles will exceed the time and effort expected in this work. So, the first step in this study has been to generate vehicle models based on publicly known information, from the vehicle technology database compiled by Argonne National Laboratory.

Objectives

- Develop a process to automatically develop models for a large number of production vehicles
- Compare the simulated vehicle energy consumption with published data on standard driving cycles
- Query, collect and process real world vehicle test data
- Compare the simulated vehicle energy consumption to real world measurements

Approach

Vehicle energy consumption can be accurately predicted on standard cycles with validated models. If a vehicle model is defined by high-level public data, the accuracy of such a model would not be as good. This study examines the level of accuracy that can be achieved by such a model on both standard and real world cycles.

We used the inputs provided by the University of Michigan as the on-road referral data for our models comparison and validation of the real word driving cycle fuel consumption: total 93027 trips recorded for 369 vehicles.

Many on-road cycles came with various issues. So, before referring to those data, we needed to (1) identify, list and fix (if needed) data issues, (2) filter out unrealistic or unfixable cycles, (3) convert on-road driving cycle data into Autonomie format and (4) add leading and trailing sections, if needed.

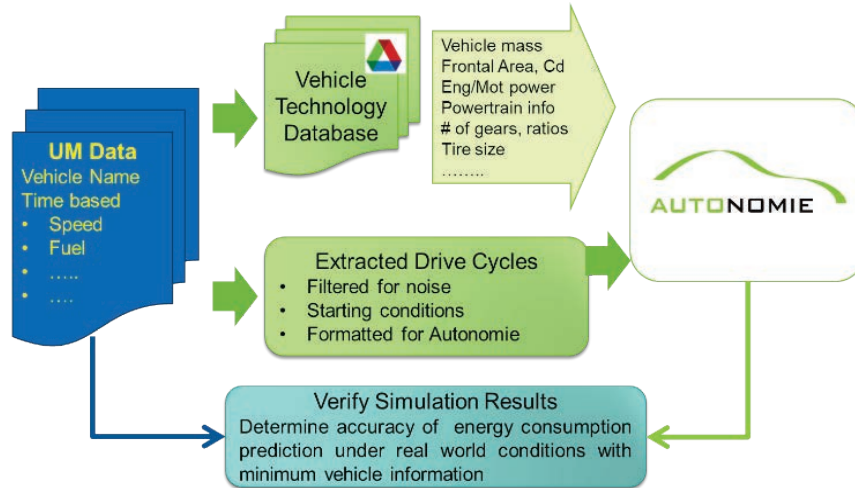


Figure VIII.2.3.1 Approach overview procedure

Results

In order to provide detailed results obtained in this study, we will focus here only on two vehicles, one conventional and a hybrid vehicle (HEV). The conventional car used here is the 2015 Honda Civic LX performing on 270 real world cycles and the HEV is the 2014 Toyota Prius Hybrid performing on 104 real world cycles. Those vehicles have been modelled on Autonomie using the publicly available vehicle data, and can predict regulatory fuel consumption within an error of +/- 5%. Since real world accessory loads were not recorded in the collected data, we assumed 600W for the accessories load during the simulations on the real world driving cycles.

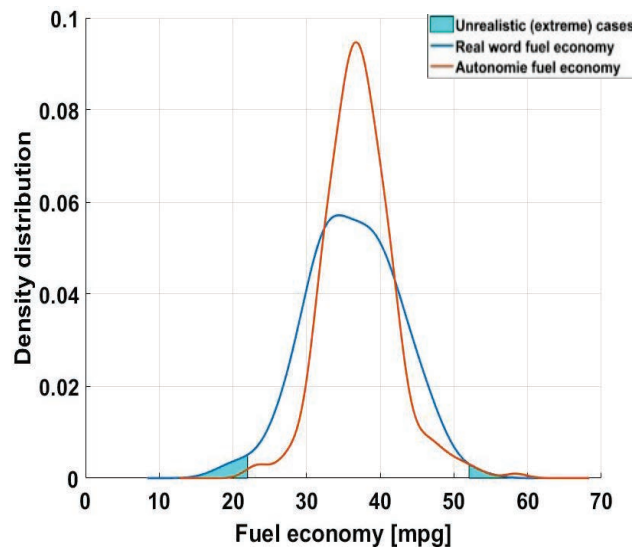


Figure VIII.2.3.2 Honda Civic fuel economy distribution

For the conventional vehicle, 45% of Autonomie’s fuel consumption predictions are within [-10%; +5%] of real world measurements. For HEV case, 53% of Autonomie’s fuel consumption predictions are within 15% margin. The following fuel economy density distribution charts help visualize how our models on real world cycles compare with the University of Michigan data acquisition. The wider distribution of the real world data shows larger variations in real world conditions during the acquisition. There are some extreme cases (blue colored zones in Figure VIII.2.3.2) that appear in the density distribution of the UofM data. However, with Autonomie’s vehicle model, 91% of the fuel economy is within [30 45] mpg which is in line with the assumptions we used for real world driving. Autonomie’s fuel economy prediction for conventional cars is overall accurate and consistent with real world measurements.

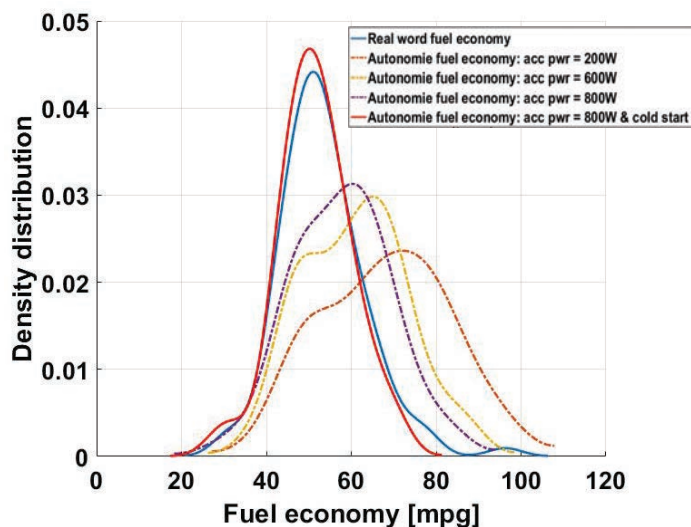


Figure VIII.2.3.3 Toyota Prius fuel economy prediction distribution vs Real world fuel economy distribution for various accessory loads

The knowledge of the accessories power during the cycle is deterministic as we can see with the Figure VIII.2.3.3: Toyota Prius fuel economy prediction distribution vs Real world fuel economy distribution for various accessory loads. Indeed, as accessories load vary from 200W to 800W, the fuel economy density distribution radically varies as well. We have also a cold start penalty in the beginning of the cycle in order to reflect the real world condition of driving. For that end, we assumed 15% fuel consumption penalty for the first 505 seconds of the cycle. Therefore, in the case of the 2014 Toyota Prius Hybrid, with the assumption of 800W power accessories and the cold start penalty applied, Autonomie’s fuel economy prediction overall matches the on-road fuel economy (red and blue plots in the Figure VIII.2.3.3).

Conclusion and next steps

In this study, the vehicles considered so far (for the manufacturing years from 2011 to 2018) are 143 conventional vehicles, 52 HEVs, 13 PHEVs and 2 EVs. The vast majority of vehicles show <10% fuel economy uncertainty on the standard driving cycles. Autonomie’s models only represent operation under ambient conditions (i.e., 72F with warmed up engine). Therefore, the lack of information on several important parameters (i.e. vehicle accessory load, outside temperature, Initial SOC) can explain the wider predictions uncertainties in certain cases. For the future data collection efforts funded by DOE, we would request the inclusion of more parameters that would help in calibrating Autonomie models.

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Acknowledgements

Severin Kamguia Simeu was the primary researcher working on this topic.

VIII.2.4 Toyota Prius Prime Validation

Project Introduction

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. 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.

Toyota Prius PHEV of which electric drive range is 25 miles. It is improved from the former version by adding a one-way clutch to the engine side which enables for generator to support electric drive. In fiscal year 2018, analysis, development and validation of the vehicle was done based on the test data from APRF of which chassis dynamometer set temperature can be controlled in a thermal chamber.

Objectives

The objective of this study is to develop and validate Prius Prime vehicle model to understand and quantify the impact of cold and hot ambient temperature on the vehicle energy consumption for new powertrain configurations.

Results

Control Analysis

To develop a vehicle model by merging the developed components model, we analyzed the vehicle-level control of Prius Prime. First, we analyzed the control algorithm based on normal temperature (or warmed-up start condition without HVAC operation), including engine on/off, battery energy management, or engine operating points, etc.

The Prius Prime as a PHEV normally depletes the electric energy first called charge depleting (CD) mode. If the battery SOC is depleted to a certain point, the vehicle is driven keeping the battery SOC called charge sustaining (CS) mode. Thanks to the one-way clutch which makes the generator connected to sun gear can support the electric driving called EV2 mode. There were no engine operation while in CD mode because of EV2 mode and larger battery size compared to the former version of Prius PHEV which shows many engine on in CD mode. As in Figure VIII.2.4.1, there is no engine on when the battery SOC is over 15%. According to the analysis, the mode change from CD to CS occurs at 14.5%.

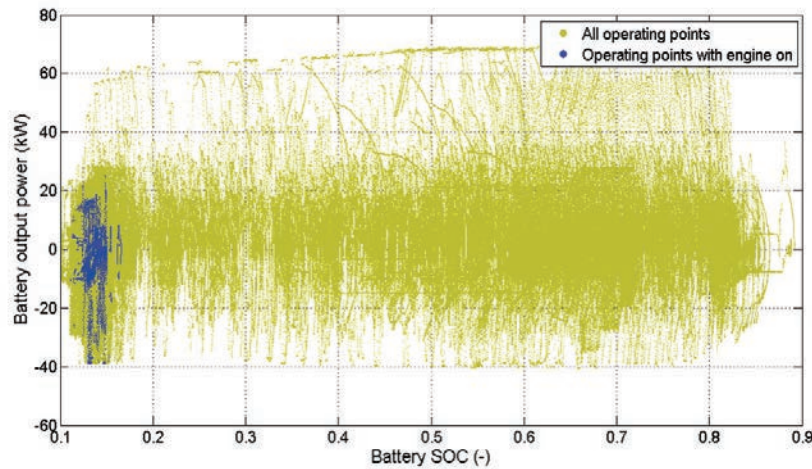


Figure VIII.2.4.1 Battery output power according to battery SOC.

After the CD or CS mode is determined, the engine on/off condition should be defined. There was no engine operation in CD mode for the Prius Prime so no need to define any engine on condition in CD mode. In CS mode, the engine on is determined by the battery SOC and power demand as in Figure VIII.2.4.2. Normally engine is turned on when the power demand is over 13kW. However, when the battery SOC decreases under 12% the engine turn on condition decreases as well to maintain the battery SOC high enough by using the engine power as a power source for the vehicle.

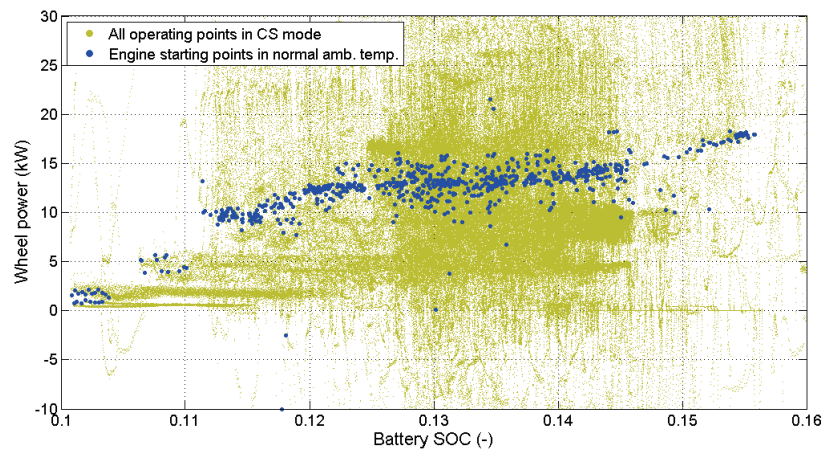


Figure VIII.2.4.2 Vehicle wheel power operating points according to battery SOC.

Once the engine is turned on, it is required to determine how to distribute the energy between engine and battery. As in Figure VIII.2.4.3, the more power is charged to the battery as the lower battery SOC. However, there is a limit of battery charging about 10kW. Therefore, battery charging when the engine is on occurs from about 14.5% of battery SOC and the charging capacity increases as the battery SOC decreases. At 13.5% battery SOC, the charging power of the battery is limited to 10kW.

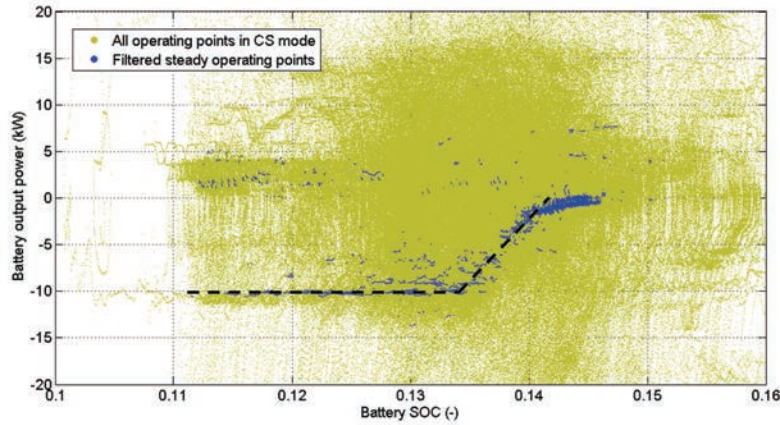


Figure VIII.2.4.3 Battery output power according to the battery SOC.

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. Figure VIII.2.4.4 shows how the main signals in the test and in the simulation compare with each other and demonstrates the successful validation of the vehicle.

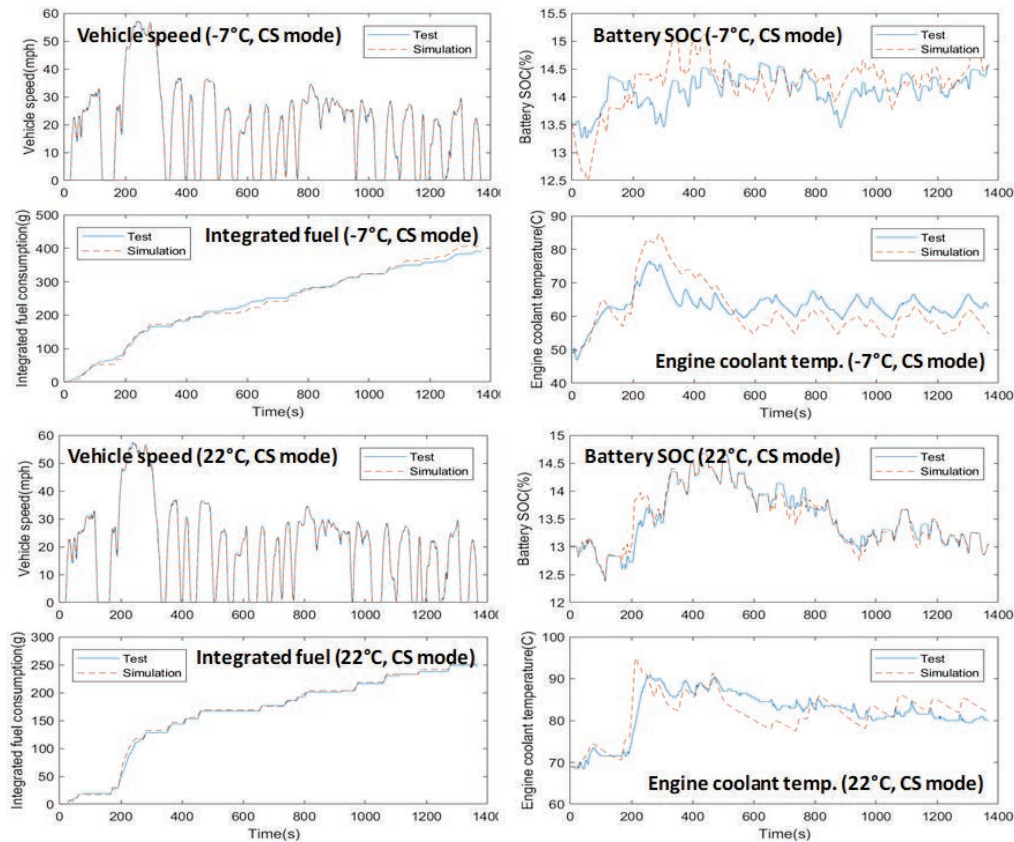


Figure VIII.2.4.4 Comparison of vehicle operating conditions (UDDS cycle, 22 °C and -7 °C ambient temperature)

Conclusions

A vehicle simulation model of the Prius Prime vehicle was developed in Autonomie based on test data from Argonne's APRF. First, the performance of the components was analyzed, including thermal aspects. Second, the vehicle supervisory control strategy under normal temperature conditions was analyzed and validated in Autonomie.

Acknowledgements

Jongreol Jeong and Namdoo Kim were the researchers focusing on this task.

VIII.3 Modeling, Simulation, and Data Analysis (NREL)

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Project Introduction

NREL-developed analytical tools and models, coupled with real-world vehicle and travel data, play a vital role in supporting and accelerating the pace of research advancements in the EEMS arena. Available for free via the NREL website, three key resources—the Transportation Secure Data Center (TSDC), the Fleet DNA repository, and the Future Automotive Systems Technology Simulator (FASTSim)—provide pivotal, integrated data and analysis capabilities for assessing and improving energy consumption and performance at multiple levels. These resources readily address several fundamental EEMS challenges—sourcing real-world data; accurately modeling large-scale systems and comprehensive scenarios; and the need for tools, techniques, and insights at vehicle, traveler, and systems levels.

Objectives

Key project objectives include:

- Working with partners to obtain and analyze real-world data for personal travel (in light-duty vehicles and other modes) and commercial vehicle travel behavior.
- Coupling real-world travel insights with agile modeling to evaluate large-scale scenarios. (NREL's long-standing competency in this arena is also applicable to off-cycle credits analysis.)
- Making research insights openly available, along with supporting data and tools, enabling independent replication and extension of research by external stakeholders.

Approach

Established in 2009, the **TSDC** provides centralized access to detailed transportation data from a wide assortment of travel surveys and studies conducted across the nation. The TSDC's two-level access approach—a public website for downloading cleansed datasets and a secure online portal for approved users to work with detailed spatial data—facilitates data availability for legitimate research while maintaining the anonymity of survey participants. Maintained by NREL in partnership with the U.S. Department of Transportation, the TSDC features millions of data points for all modes of travel, including second-by-second global position system (GPS) readings, vehicle characteristics (if applicable), and demographics. NREL

screens the initial data for quality control, translates each data set into a consistent format, and interprets the data for spatial analysis. NREL's processing routines add information on vehicle fuel economy and road grades and join data points to the road network.

Established in 2012, the **Fleet DNA** clearinghouse now features over 12 million miles of high-fidelity vehicle and operations data from more than 1,800 medium- and heavy-duty vehicles, including delivery vans and trucks, school buses, transit buses, bucket trucks, service vans, tractor trailers, and refuse trucks. Aggregated duty cycle statistics, summaries, and visualizations are available for download via the public website while a secure database stores and protects the raw data. Fleet DNA can be combined with other models, tools, and data resources, and subjected to data fusion, multivariate analysis, and advanced visualization techniques to investigate complex, multi-dimensional transportation issues and solutions. For example, Fleet DNA data can be fused with datasets pertaining to chassis dynamometer results, road networks, road grade, weather, vehicle specifications, and vehicle registrations, and combined with other tools such as FASTSim and the Drive-Cycle Rapid Investigation, Visualization, and Evaluation (DRIVE) analysis tool, which uses GPS and controller area network (CAN) data to characterize vehicle operation and produce statistically representative drive cycles based on real-world activity.

Building upon NREL's decades of experience with vehicle powertrain modeling, **FASTSim** provides an easy way to compare powertrains and estimate the impact of technology improvements on light-, medium-, and heavy-duty vehicles. Balancing accuracy and complexity, it captures the most important factors influencing vehicle fuel economy, performance, and cost—including powertrain technology, vehicle and component sizes, how the vehicle is driven, etc. It accommodates a range of vehicle types—conventional (spark ignition, Atkinson, diesel, and hybrid diesel), electric-drive (hybrid, plug-in hybrid, and all-electric), and hydrogen fuel cell vehicles—and includes standard U.S. drive cycles as well as European and Japanese cycles (plus the ability to link to on-road drive cycles from the TSDC and Fleet DNA).

Results

The **TSDC** continues to see substantial growth in the number of external users (the public website currently has more than 2,000 registered users while the secure data portal has roughly 100) as well as the number of datasets, with efforts underway to secure additional datasets. Redesigned to accommodate an ever-increasing number of datasets, the revamped public website features an enhanced user experience with a one-time login functionality, an interactive map, a sortable and searchable table, and a landing page for each dataset—all within a responsive design template that accommodates viewing via mobile devices. To ensure a positive experience for users of the secure portal as well, NREL developed a questionnaire to solicit feedback at two points during each user's access period.

To further increase the TSDC's reach, NREL hosted a hands-on workshop titled “Open Travel Data: Demo of Analysis Potential with the TSDC” at the GIS for Transportation Symposium in March 2018. Additionally, a new [TSDC GitHub repository](#) houses tutorials and demonstrations of how faculty, students, national lab researchers, and others can utilize the data.

Nearly 150 research publications have been supported through access to TSDC data, across a wide range of applications. Example research areas supported by TSDC data include:

- Real-world driving and parking profiles used to inform charging infrastructure siting based on potential future vehicle penetration scenarios.
- Analysis of the prevalence of driving conditions detrimental to vehicle emissions control (NREL conducted this work in collaboration with industry partners).

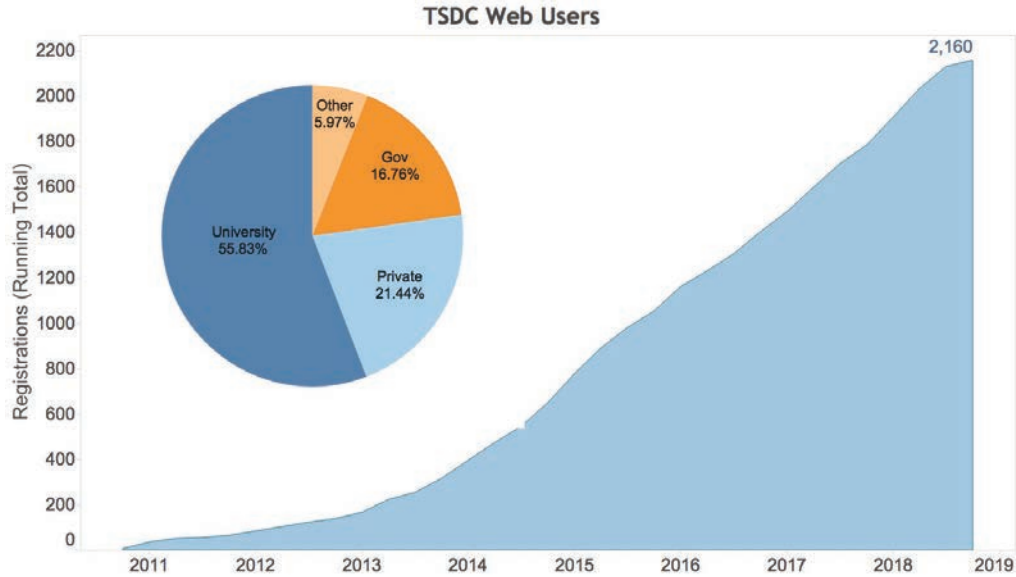


Figure VIII.3.1 The TSDC boasts a growing number of registrants from various backgrounds, primarily academia, government, and private industry. Credit: NREL

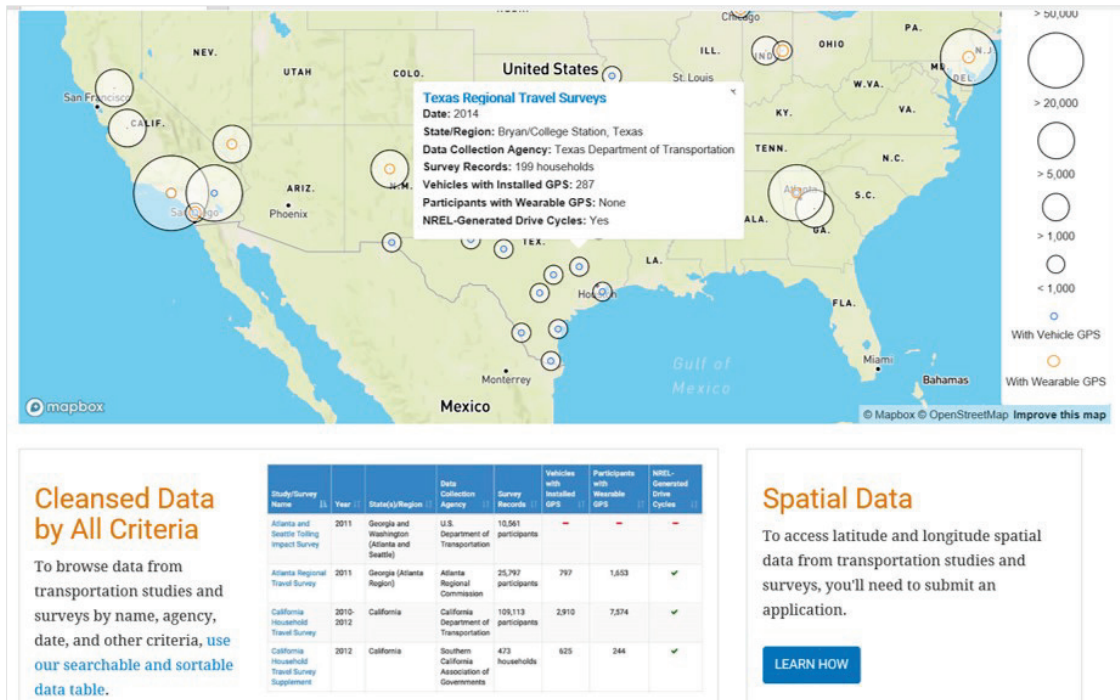


Figure VIII.3.2 The TSDC's public website, which underwent a major redesign in FY 2018, offers cleansed data for download while a secure portal provides approved users with access to spatial data. Credit: NREL

The **Fleet DNA** clearinghouse features 1-Hz engine CAN, GPS, and component data from commercial vehicles operated by project partners across the country. New this year are 14 datasets from UPS; Walmart; Zion and Bryce Canyon national parks; the ports of Long Beach, New York, and New Jersey; Mexico City; the U.S. Army Tank Automotive Research, Development, and Engineering Center (automated vehicles); Odyne; Rialto School District; Duluth and Santa Clara Valley transit authorities; and the NREL shuttle fleet. In addition to securing and processing these new datasets, NREL made significant improvements related to data

processing, scalability, and access. The new Spark big-data platform enables operation on the full data package and provides new capabilities to filter signals, quickly query for available data, work with missing values, and much more. Its consistent data structure makes sharing data easier, and the platform is highly scalable with increasing quantities of data. NREL also launched an updated version of the [DriveCAT drive cycle analysis tool](#), with over 30 representative downloadable drive cycles developed from Fleet DNA data.

Fleet DNA's extensive, real-world data help users understand the broad operational range of commercial vehicles across vocations, technologies, and weight classes and enable the successful development of energy-efficient vehicle technologies that meet performance requirements and reduce operating costs. The data-driven insight and decision-making capabilities facilitated by Fleet DNA support a variety of DOE-funded research activities and partnerships, including recent work with industry partners Cummins, Robert Bosch, Peterbilt, Volvo, Ford, Eaton, Proterra, Navistar, Blue Bird, Efficient Drivetrains, PACCAR, and Odyne.

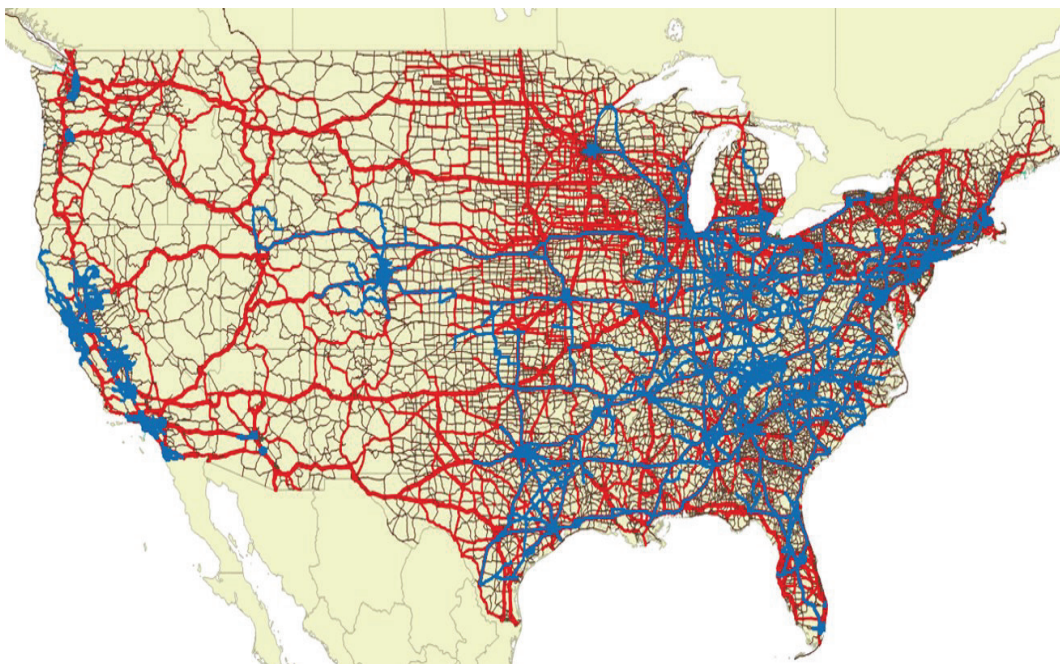


Figure VIII.3.3 Map showing freight volumes (red) along major U.S. roadways and Fleet DNA data coverage (blue) along those routes. Credit: NREL

The following examples highlight recent projects that leveraged Fleet DNA:

- Fleet DNA supported several research projects led by two pillars within DOE's Systems and Modeling for Accelerated Research in Transportation (SMART) initiative—a multi-modal pillar project used Fleet DNA delivery truck data collected from UPS trucks in Columbus, Ohio; and a connected and automated vehicles pillar project tapped into detailed platooning test results combined with national usage data from Volvo trucks.
- In partnership with the Cummins and PACCAR Super Truck II teams and Purdue University's ARPA-E NEXTCAR team, NREL fused Fleet DNA data from class 8 tractor trailers with road network data, employing data mining and analysis techniques to support optimized and connected powertrain development subject to real-world driving conditions.
- In partnership with Blue Bird, NREL utilized Fleet DNA school bus data for drive cycle development and baseline EV chassis dynamometer testing to aid in the development of a next-generation, high-efficiency, electric school bus with vehicle-to-grid power export capabilities.

- NREL employed Fleet DNA data analytics to 1) improve the Environmental Protection Agency’s Motor Vehicle Emission Simulator (MOVES) by providing idle, soak, and speed distributions across vocations and weight classes and 2) develop low-load NOx emission profiles for the California Air Resources Board in partnership with the Southwest Research Institute.
- Industry partners Cummins and Robert Bosch are utilizing representative drive cycles developed from Fleet DNA data using the DRIVE tool in their development of commercially viable, range-extended electric vehicles for urban delivery applications, targeting efficiency improvements of 50%.

NREL continues to validate and enhance **FASTSim**, now available for download on the NREL website in Excel and Python formats along with a recently published FASTSim Validation Report, a new introductory fact sheet, and an assortment of technical papers (70 listed on the website to date) describing research projects that made use of the tool.

FASTSim has played an important role in a wide variety of NREL research projects and industry partnerships this year, contributing to efforts in real-world modeling, powertrain optimization, thermal modeling, fuel-economy estimations, eco-adaptive controls, eco-routing, energy-aggregation analyses, off-cycle technology evaluations, battery life and charging infrastructure analyses, optimized fleet operation, and economic evaluations, among other topics.

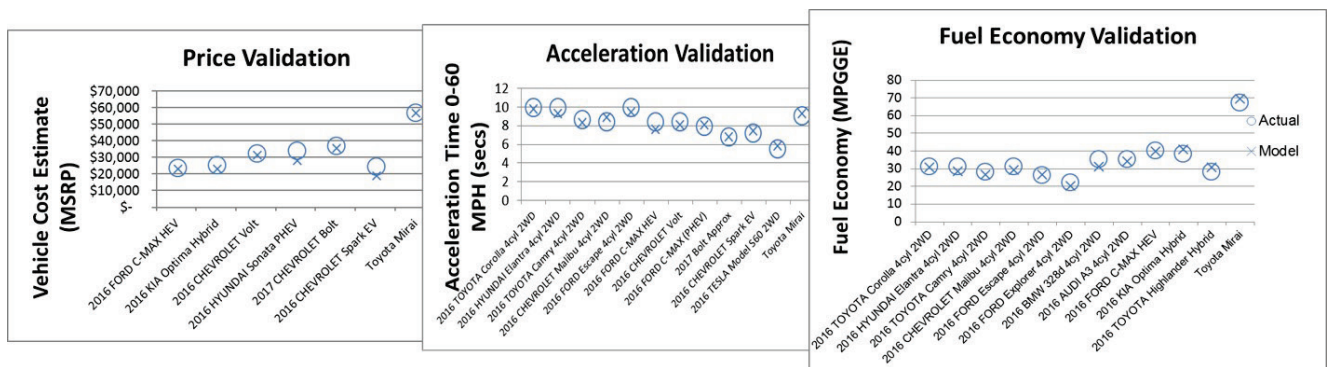


Figure VIII.3.4 FASTSim validation efforts focus on price, acceleration, and fuel economy. Credit: NREL

While the TSDC, Fleet DNA, and FASTSim can be used independently, in combination they offer compounded benefits and insights, as in these recent cases:

- Segregation and analysis of vehicle speed profiles in different driving conditions as well as simulation for various vehicle/powertrain types – Used to train energy estimation modeling for green routing and aggregate off-cycle technology impact assessments, including for connected and automated vehicles.
- Large-scale screening of prospective vehicle dynamics and powertrain control strategies prior to implementation by a major automaker.
- Opportunity assessment for commercial vehicle electrification – Worked with multiple industry partners to optimize hybrid electric, all-electric, and range-extended EV powertrain requirements using FASTSim models simulated across a distribution of real-world vocational drive cycles and operational modes from Fleet DNA.

Conclusions

Valuable EEMS resources, the TSDC, Fleet DNA, and FASTSim provide vital real-world data and analysis capabilities for assessing and optimizing current and future vehicle/transport energy consumption and

performance. While protecting individual privacy and commercially sensitive data, NREL makes these tools easily accessible—open source and free of costs associated with licensing and 3rd party software—to researchers at NREL and at large, maximizing their value to the national laboratory system, U.S. industry, and ultimately the American consumer.

Combining these tools enables agile, large-scale, cost-effective scenario evaluations, drawing on validation and real-world data for credibility and focusing on the most influential effects and fidelity required for a given task. Over the course of the year, these tools have been applied in numerous DOE evaluations pertaining to advanced powertrains, connected/automated vehicles, and alternative fuel infrastructure as well as industry partnerships focusing on the assessment of off-cycle technology and alternative powertrain design scenarios.

Key Publications

A wide assortment of research projects, at NREL and beyond, have tapped into these resources. Many resulting publications are available via the TSDC, Fleet DNA, and FASTSim websites. The following list provides a few specific examples:

1. Duran, A., Phillips, C., Perr-Sauer, J., Kelly, K. et al., "Leveraging Big Data Analysis Techniques for U.S. Vocational Vehicle Drive Cycle Characterization, Segmentation, and Development," SAE Technical Paper 2018-01-1199, 2018, <https://doi.org/10.4271/2018-01-1199>.
2. Duran, A., Li, K., Kresse, J., and Kelly, K., "Development of 80- and 100- Mile Work Day Cycles Representative of Commercial Pickup and Delivery Operation," SAE Technical Paper 2018-01-1192, 2018, <https://doi.org/10.4271/2018-01-1192>.
3. Lammert, M., Bugbee, B., Hou, Y., Mack, A., et al., "Exploring Telematics Big Data for Truck Platooning Opportunities," SAE Technical Paper 2018-01-1083, 2018, <https://doi.org/10.4271/2018-01-1083>.
4. Jehlik, F., Chevers, N., Moniot, M., Song, Y., et al., "Determining Off-Cycle Fuel Economy Benefits of 2-Layer HVAC Technology," SAE Technical Paper 2018-01-1368, 2018, <https://doi.org/10.4271/2018-01-1368>.
5. Hamza, K., and Laberteaux, K., "A Study on Optimal Powertrain Sizing of Plug-In Hybrid Vehicles for Minimizing Criteria Emissions Associated with Cold Starts," SAE Technical Paper 2018-01-0406, 2018, <https://doi.org/10.4271/2018-01-0406>.
6. Holden, J., Van Til, H., Zhu, L., Wood, E., Shirk, M., and Gonder, J., "Trip Energy Estimation Methodology and Model Based on Real-World Driving Data for Green Routing Applications," *Transportation Research Record: Journal of the Transportation Research Board*, September 2018. doi.org/10.1177/0361198118798286
7. Wood, E., Gonder, J., and Jehlik, F., "On-Road Validation of a Simplified Model for Estimating Real-World Fuel Economy," *SAE Int. J. Fuels Lubr.* 10(2):528-536, 2017, <https://doi.org/10.4271/2017-01-0892>.
8. Chen, Y., Hu, K., Zhao, J., et al., "In-Use Energy and CO2 Emissions Impact of a Plug-In Hybrid and Battery Electric Vehicle Based on Real-World Driving," *Int. J. Environ. Sci. Technol.* (2017). <https://doi.org/10.1007/s13762-017-1458-0>.
9. Laberteaux, K., and Hamza, K., "Highlighting the Differential Benefit in Greenhouse Gas Reduction via Adoption of Plug-In Hybrid Vehicles for Different Patterns of Real Driving," SAE Technical Paper 2017-01-1178, 2017, <https://doi.org/10.4271/2017-01-1178>.
10. Laberteaux, K., and Hamza, K., "A Study of Greenhouse Gas Emissions Reduction Opportunity in Light-Duty Vehicles by Analyzing Real Driving Patterns," SAE Technical Paper 2017-01-1162, 2017, <https://doi.org/10.4271/2017-01-1162>.

11. Jehlik, F., Iliev, S., Wood, E., and Gonder, J., "Investigation of Transmission Warming Technologies at Various Ambient Conditions," SAE Technical Paper 2017-01-0157, 2017, <https://doi.org/10.4271/2017-01-0157>.

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