NATIONAL RENEWABLE ENERGY LABORATORY

40

1977 - 2017





Automated, Connected, Electrified and Shared (ACES) Transportation Modeling and Analysis at NREL

Jeff Gonder, Group Manager

Mobility, Behavior and Advanced Powertrains

NREL Transportation & Hydrogen Systems Center

June 2018

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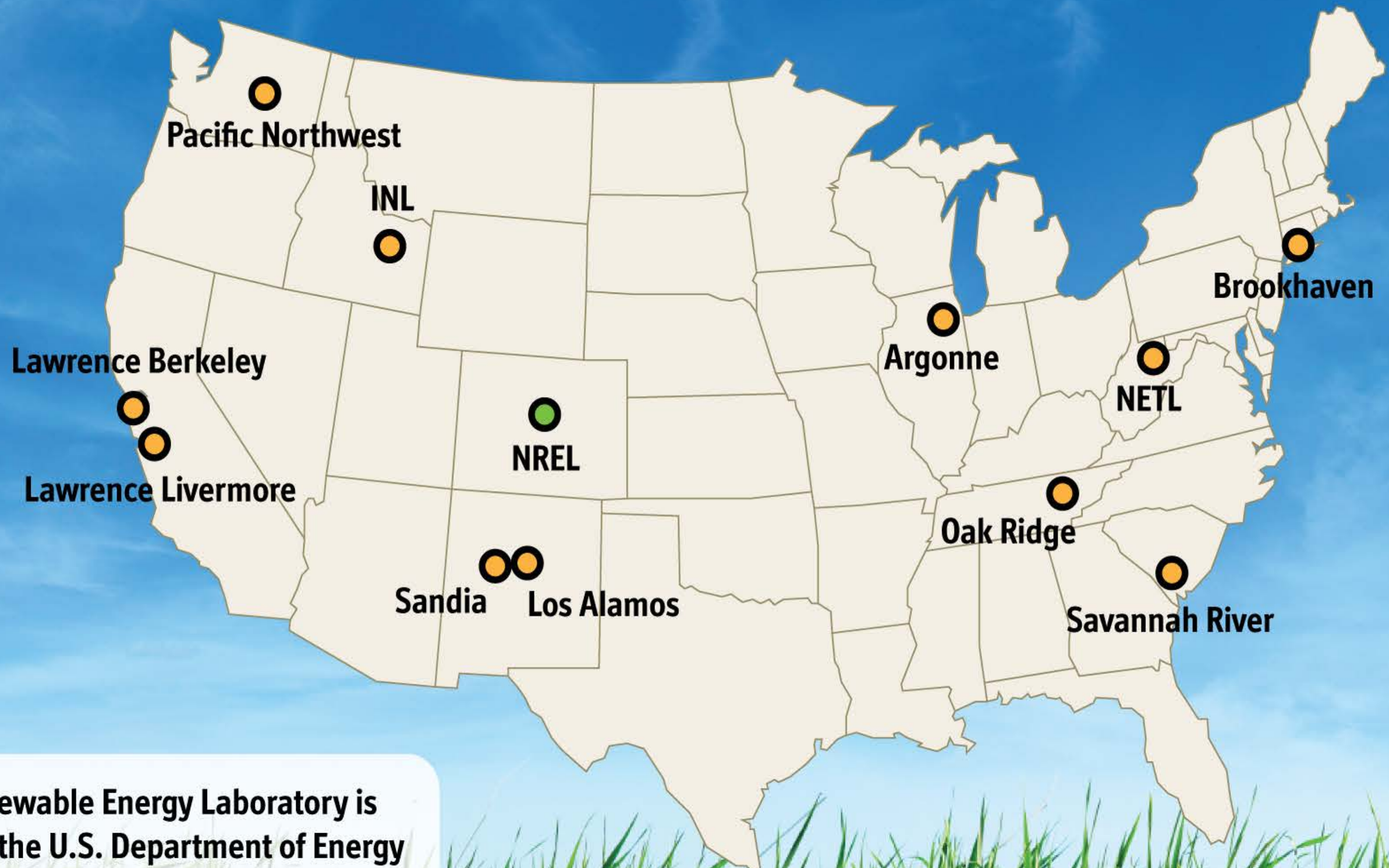


National Renewable Energy Laboratory is operated for the U.S. Department of Energy by the Alliance for Sustainable Energy, LLC

Scope of NREL Mission

Sustainable Transportation

- Vehicle & Mobility Technologies
- Electrification
- Hydrogen
- Biofuels

Energy Productivity

- Residential Buildings
- Commercial Buildings
- Manufacturing

Renewable Electricity

- Solar
- Wind
- Water: Marine Hydrokinetics
- Geothermal

Systems Integration

- Grid Integration of Clean Energy
- Distributed Energy Systems
- Batteries and Thermal Storage
- Energy Analysis

Partners

- Private Industry
- Federal Agencies
- State/Local Government
- International

ENERGY EFFICIENT MOBILITY SYSTEMS PROGRAM INVESTIGATES

MOBILITY ENERGY PRODUCTIVITY

THROUGH FIVE EEMS ACTIVITY AREAS

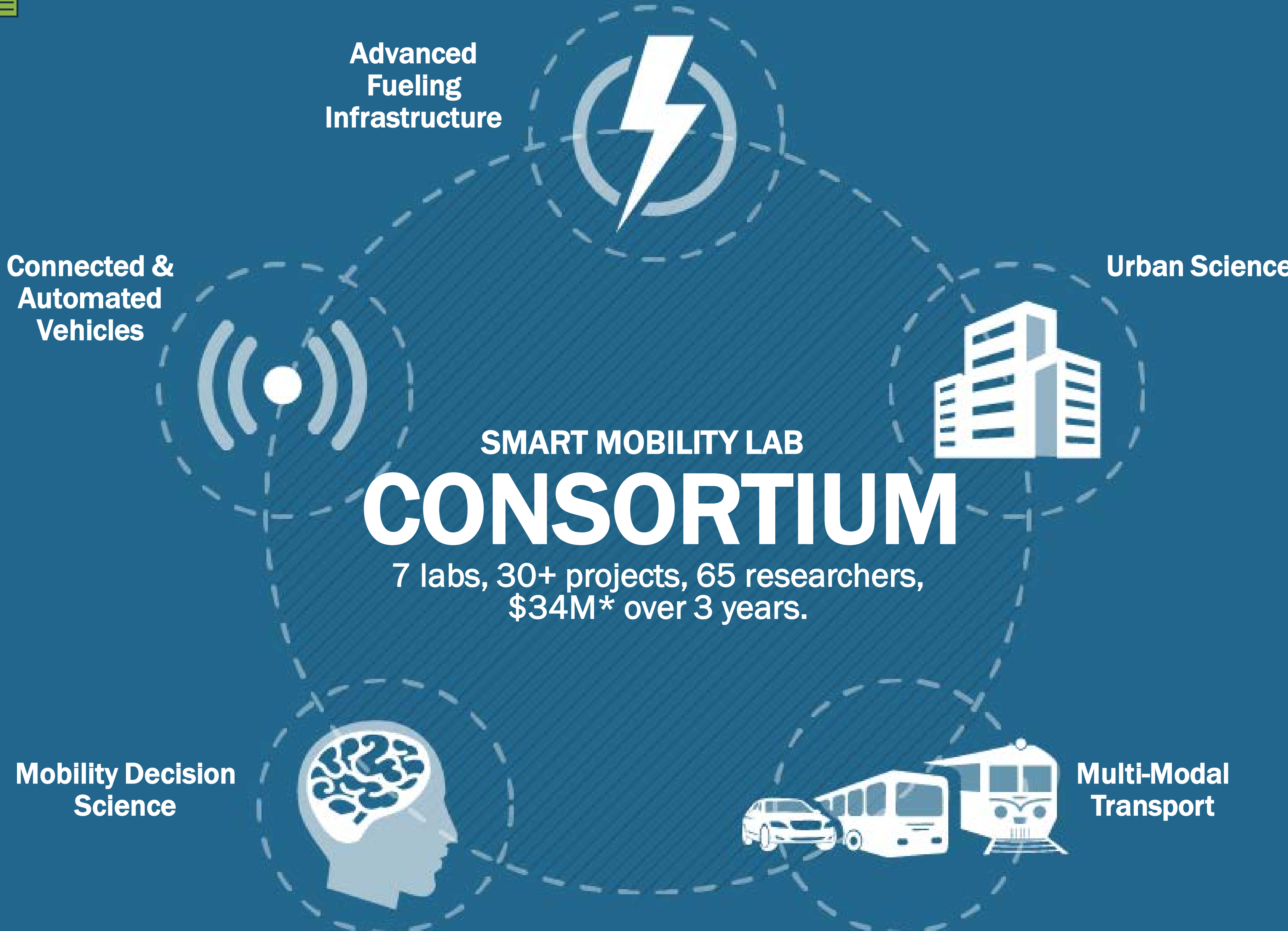
Advanced R&D Projects

Living Labs

Smart Mobility Lab Consortium

Core Evaluation & Simulation Tools

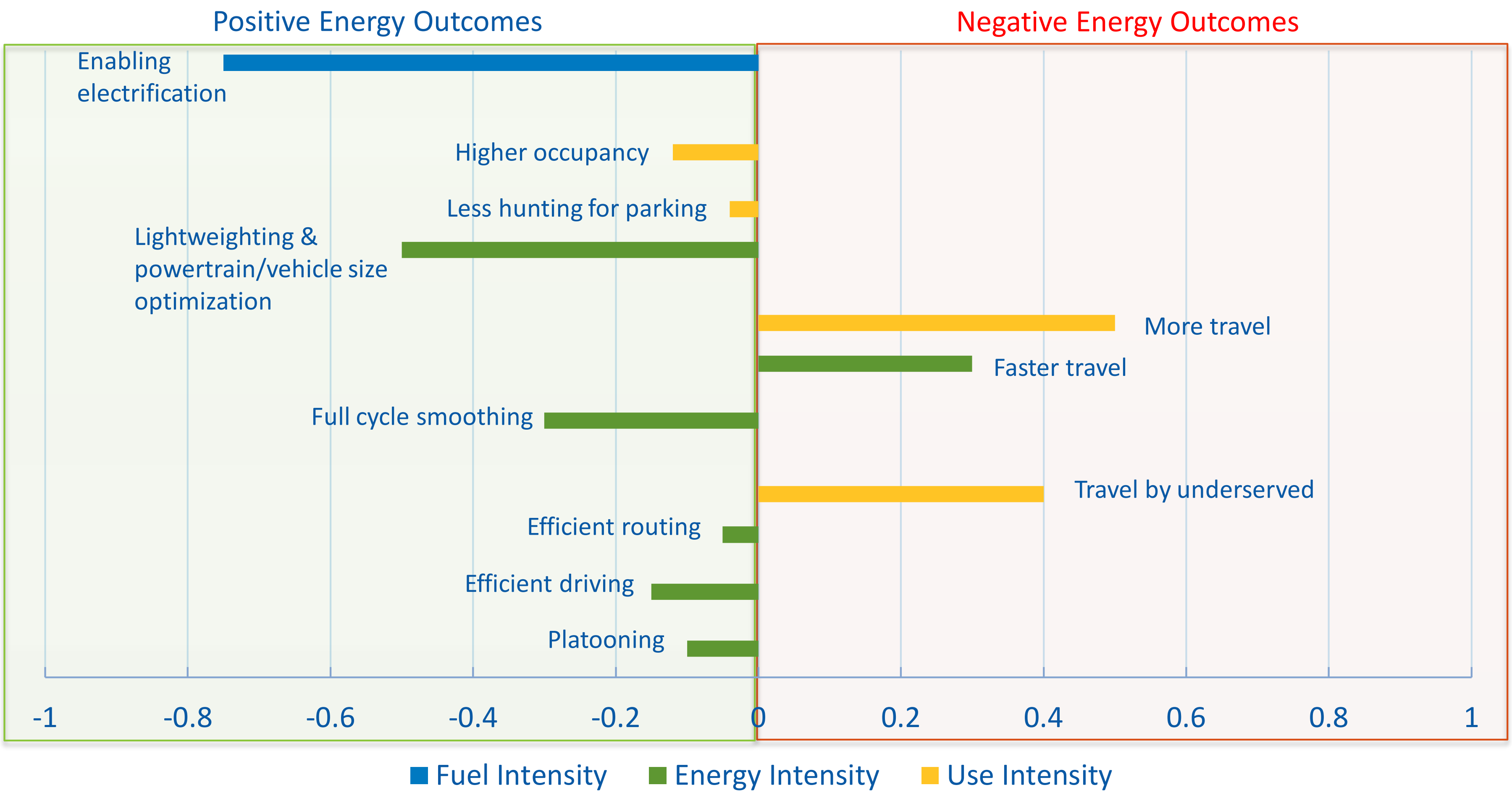
HPC4Mobility & Big Transportation Data Analytics



*Based on anticipated funding

CAV Energy Impacts: “Bookending” Analyses

- Potential connected and automated vehicle (CAV) features could have dramatic energy impacts

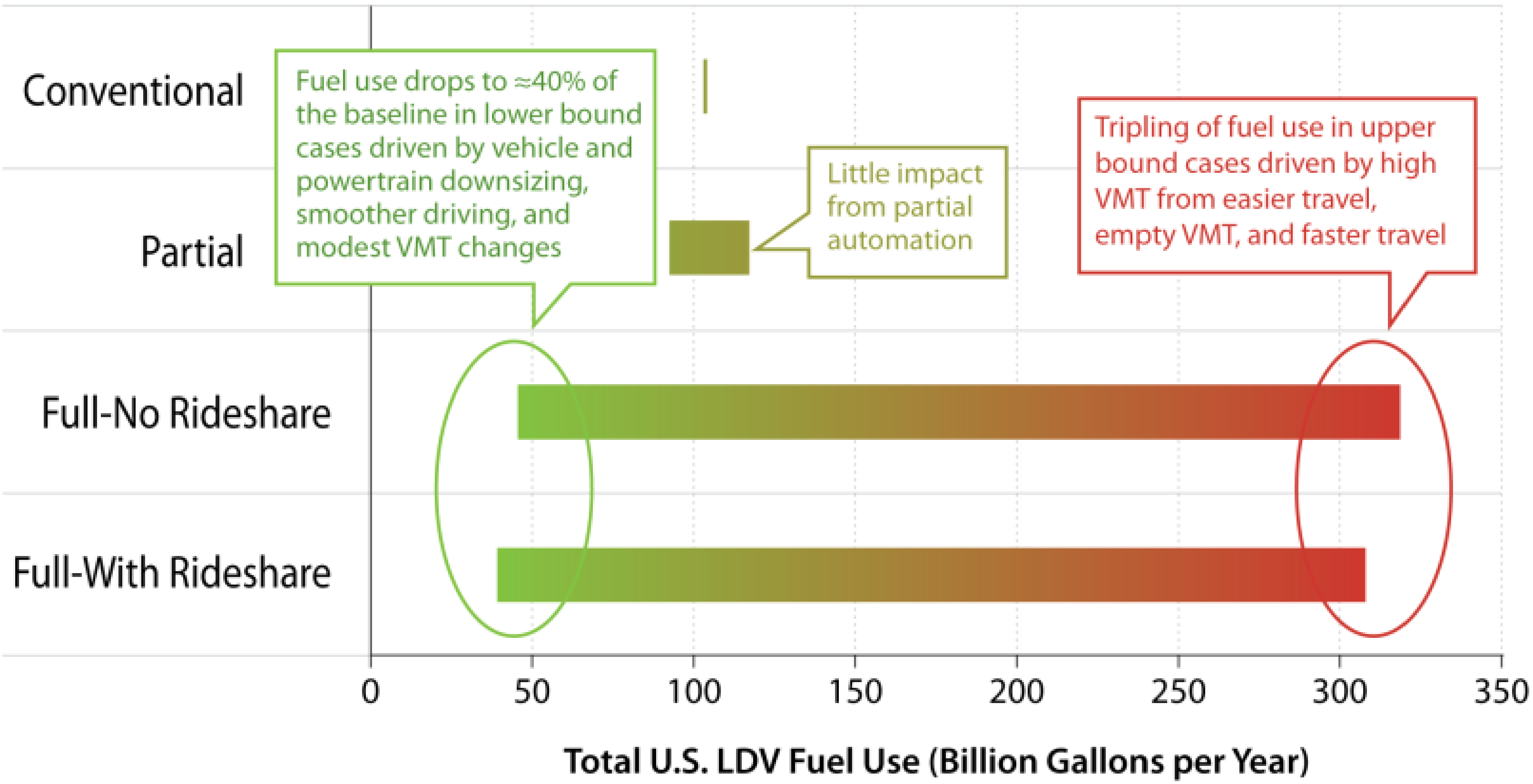


Brown, A.; Gonder, J.: Repac, B. (2014). “An Analysis of Possible Energy Impacts of Automated Vehicles.” Chapter 5, Societal and Environmental Impacts. Meyer, G., ed*. Lecture Notes in Mobility: Road Vehicle Automation.* Berlin: Springer. doi: 10.1007/978-3-319-05990-7_13

Wide Range of National-Level CAVs Impacts Scenarios

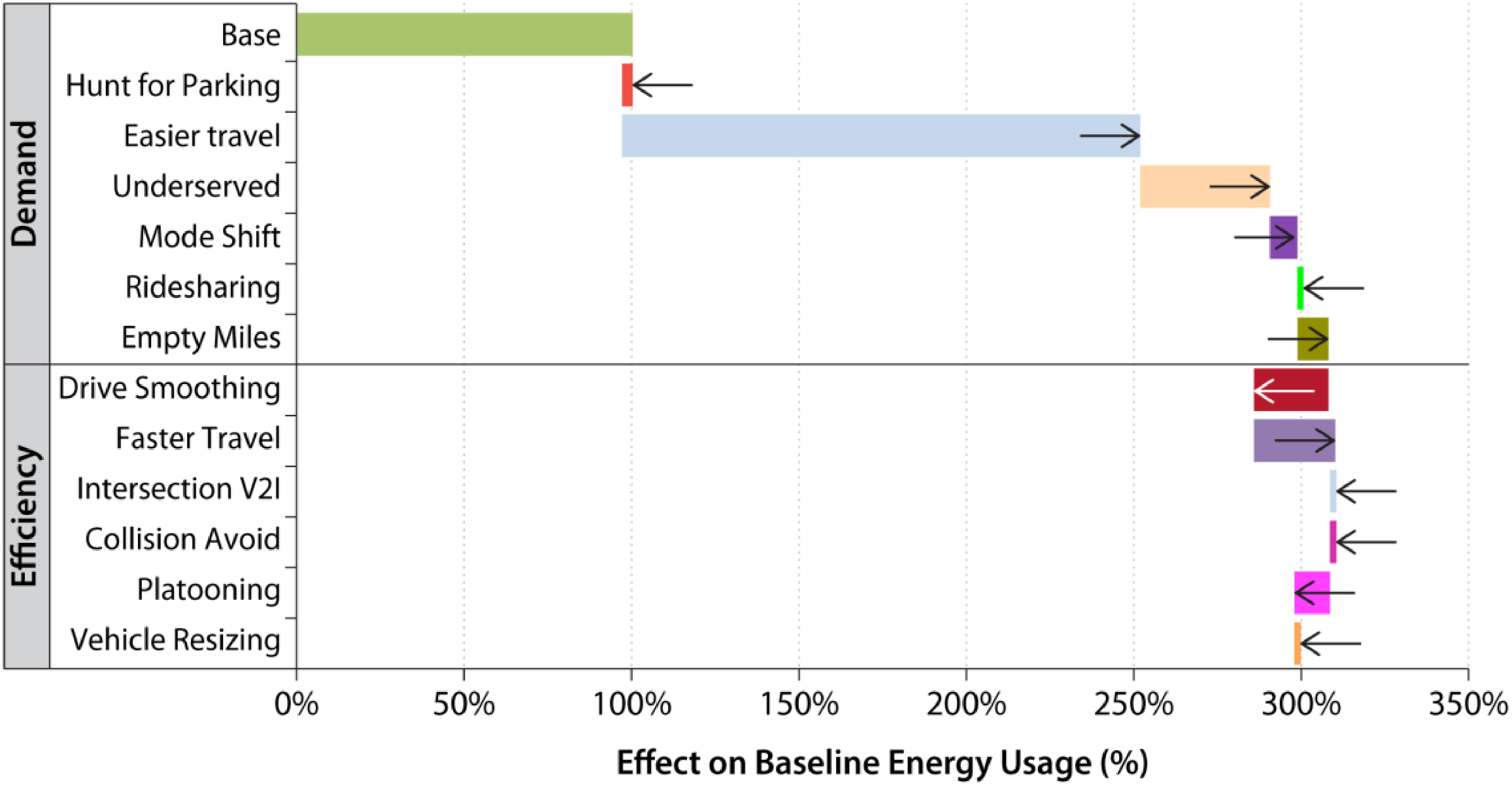
- Partial automation: +/- 10%-15%
- Full automation: -60% / +200%
- Ride-sharing: Reduction of up to 12%

(No fuel switching or electrification included)

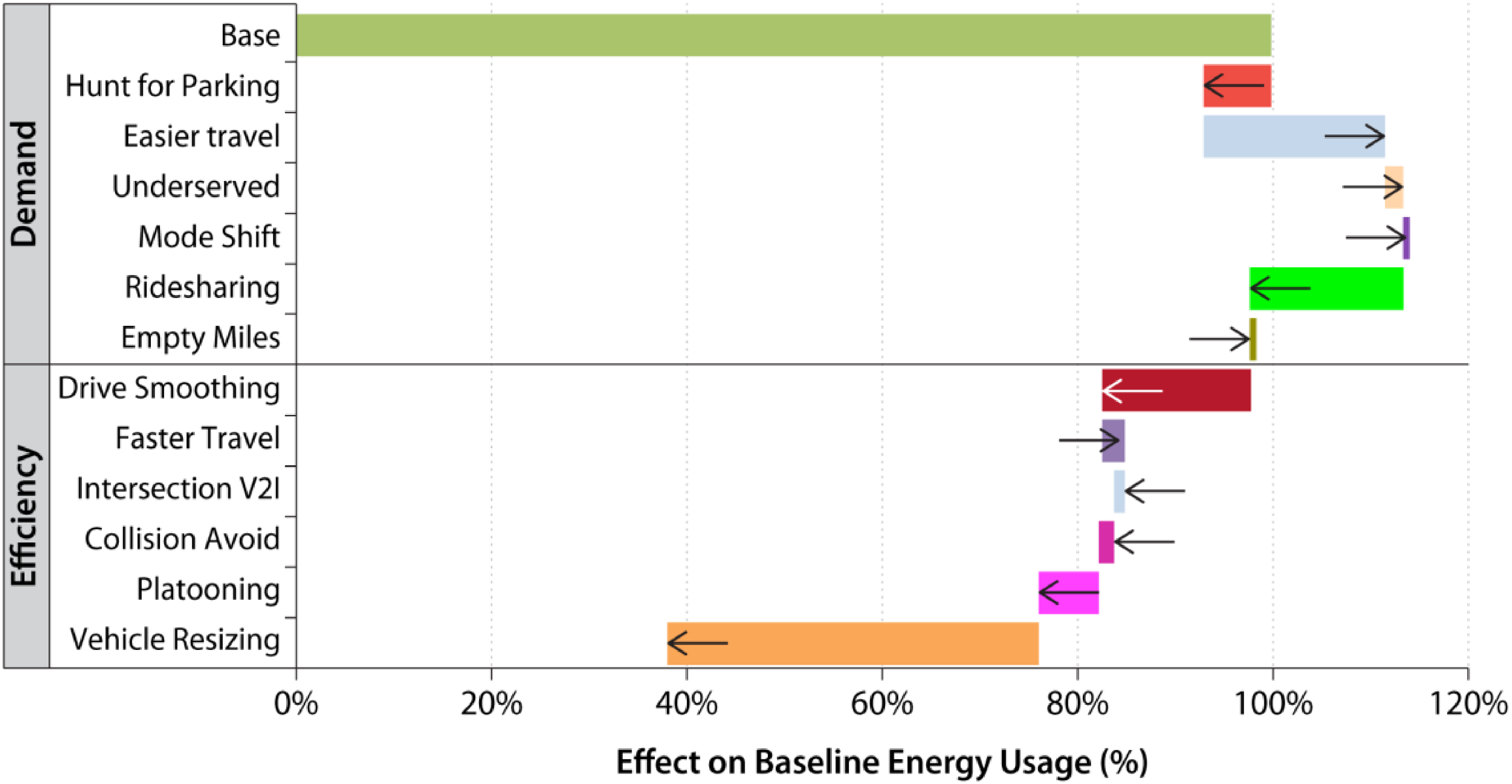


Stephens, T.S.; Gonder, J.; Chen, Y.; Lin, Z.; Liu, C.; Gohlke, D. "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles." *NREL Technical Report, TP-5400-67216, Nov. 2016.* www.nrel.gov/docs/fy17osti/67216.pdf

Upper Bound Scenario Details

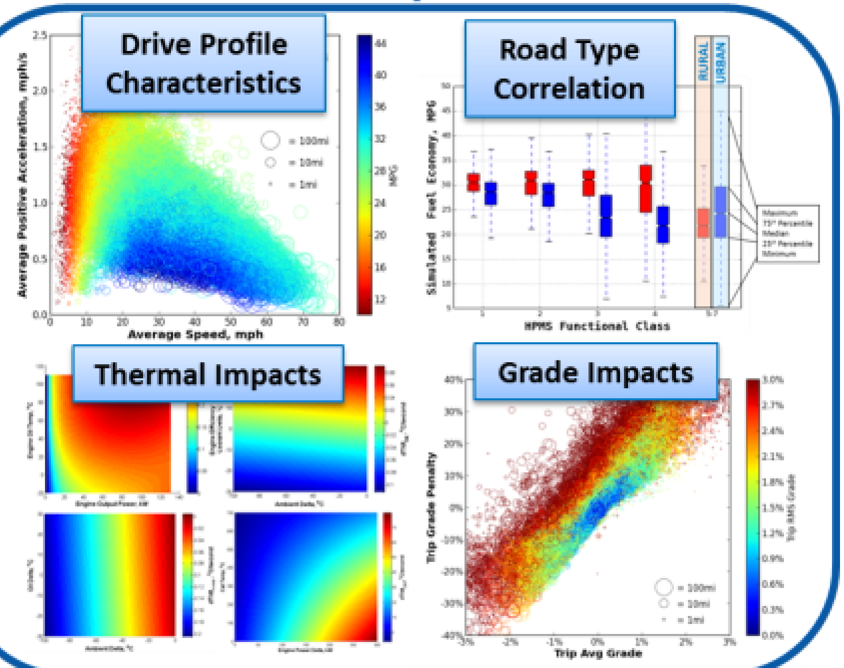


Lower Bound Scenario Details



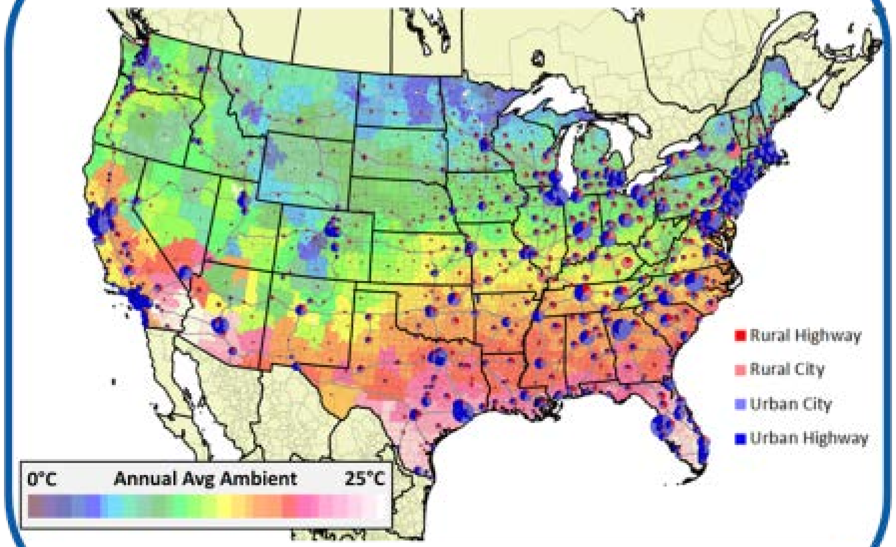
Bottom-Up Approach to Explore Nuanced Scenarios

Fuel Consumption *Rates*



Quantify different CAV feature fuel economy impacts in different driving situations

Vehicle Miles Traveled (VMT) *Volumes*



Consider the relative proportion of national VMT represented by each driving situation

- Aggregate weighted results for national-level impact, making A/B comparisons for fuel use with or without a given technology active

Objectives for Bottom-Up Approach

Fuel Consumption Rate (FCR) by Driving Condition	✖	Vehicle Miles Traveled (VMT) by Driving Condition

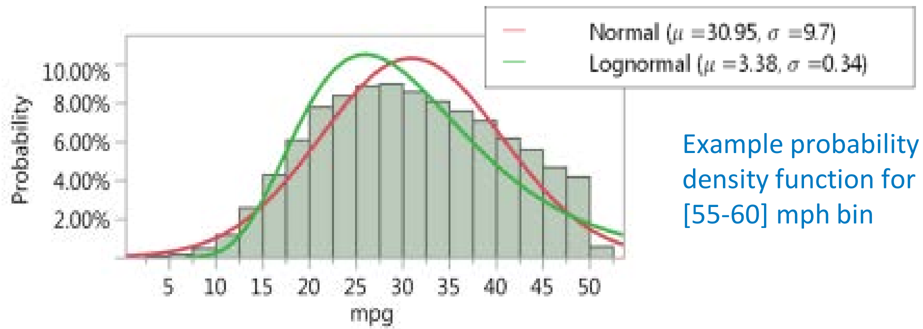
Repeat for Scenario A and Scenario B to determine relative differences

- Same philosophy as calculation architecture for EPA MOVES
- Desired framework attributes for CAVs analysis application
  - Customizable: able to represent today's baseline and future scenarios with different powertrain and CAV technology mixes (for which both the FCR and VMT matrices may change)
  - Flexible: able to receive inputs from the variety of different tasks across SMART (including both models and data)
  - Tractable: model/data inputs in the format desired for national-level calculations can be obtained
  - Appropriately sensitive: desire FCR and VMT disaggregation in dimensions where variation expected between the examined scenarios
  - Defensible: demonstrate that roll up approach applied at different geographic scales shows consistency with test data and detailed modeling

Initial testing to confirm customizability, flexibility, tractability, sensitivity and defensibility

- Example for fuel consumption matrix determination—can populate from different sources and examine different constructs (provided corresponding VMT disaggregation is possible*):

Distribution of fuel consumption for each speed & road type bin based on a large set of real world drive cycles from the TSDC simulated in FASTSim.



Example probability density function for [55-60] mph bin

Fit normal distribution (best fit after statistical testing) of fuel consumption rate for each bin.

Representative conventional vehicle fuel economy (mean of distribution per speed bin, in gallons per 100 miles)

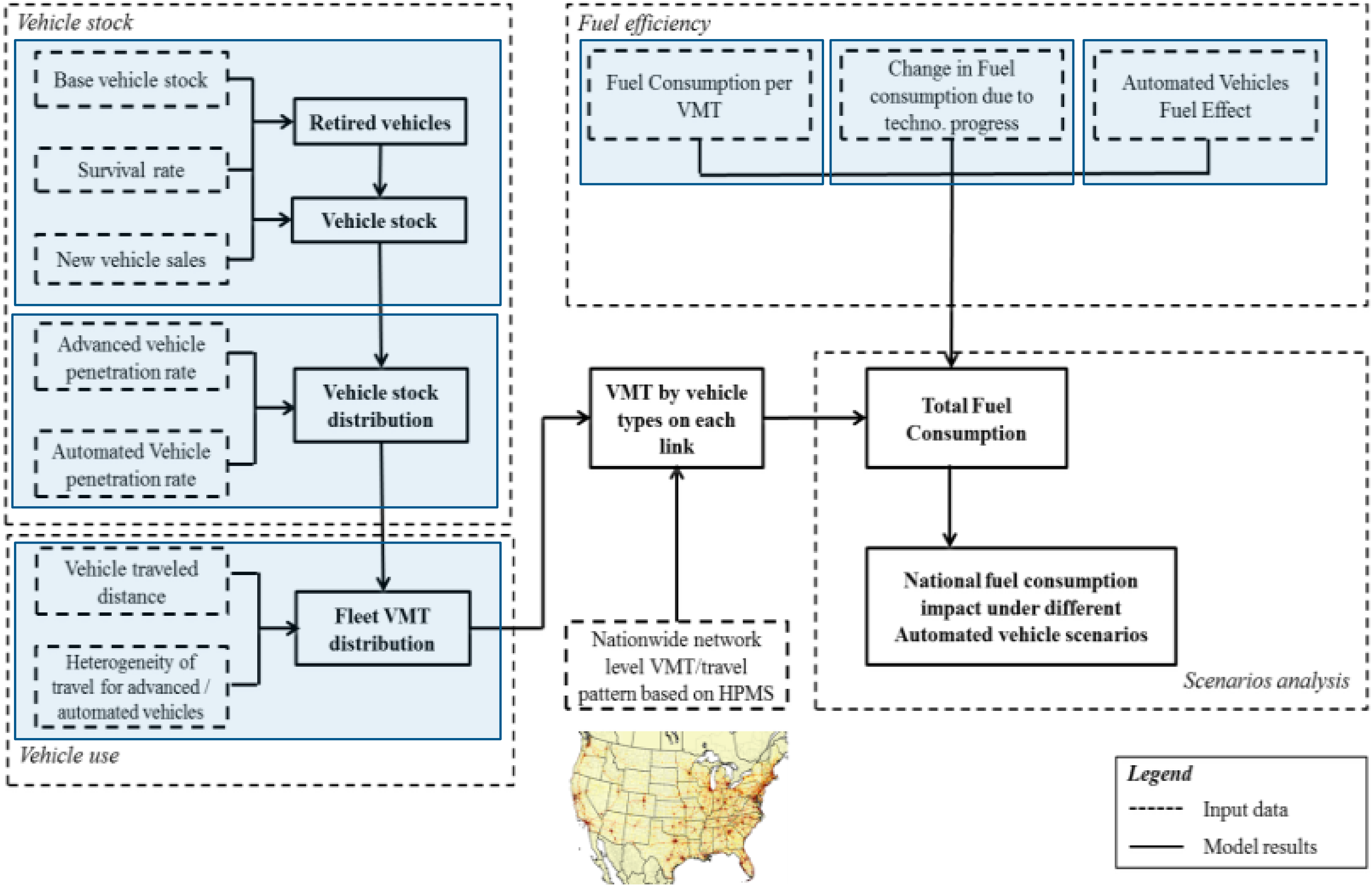
Same process with other vehicle types; adjust over time based on macro scenario trends

	freeways & highways		connectors & arterials		local roads	
Avg Speed mph	Rural	Urban	Rural	Urban	Rural	Urban
[0-5]						10.97
(5-10]				10.37	8.95	10.67
(10-15]			7.63	8.21	6.87	7.55
(15-20]			7.34	7.64	6.39	6.95
(20-25]			6.55	6.71	5.85	6.25
(25-30]		4.74	5.77	5.86	5.22	5.39
(30-35]		4.4	4.98	4.99	4.67	4.55
(35-40]		4.26	4.42	4.35	4.15	4.04
(40-45]	4.27	4.16	4.06	3.98	3.71	3.79
(45-50]	3.86	3.91	3.61	3.81	3.58	3.68
(50-55]	3.34	3.69	3.66	3.69	3.44	3.67
(55-60]	3.08	3.5	3.49	3.51	3.26	3.59
(60-65]	3.16	3.44	3.44	3.41	3.32	
(65-70]	3.33	3.52	3.49	3.53		
(70-75]	3.49	3.65	3.53	3.6		
(75-80]	3.76					
>80						

*For example shown see: Kaushik, K.; Wood, E.; Gonder, J. "Coupled Approximation of U.S. Driving Speed and Volume Statistics Using Spatial Conflation and Temporal Disaggregation." Forthcoming in *Transportation Research Record: Journal of the Transportation Research Board*; TRB Paper 18-06756.

TSDC = Transportation Secure Data Center; FASTSim = Future Automotive Systems Technology Simulator

National Level Analysis Framework Calculation Flows

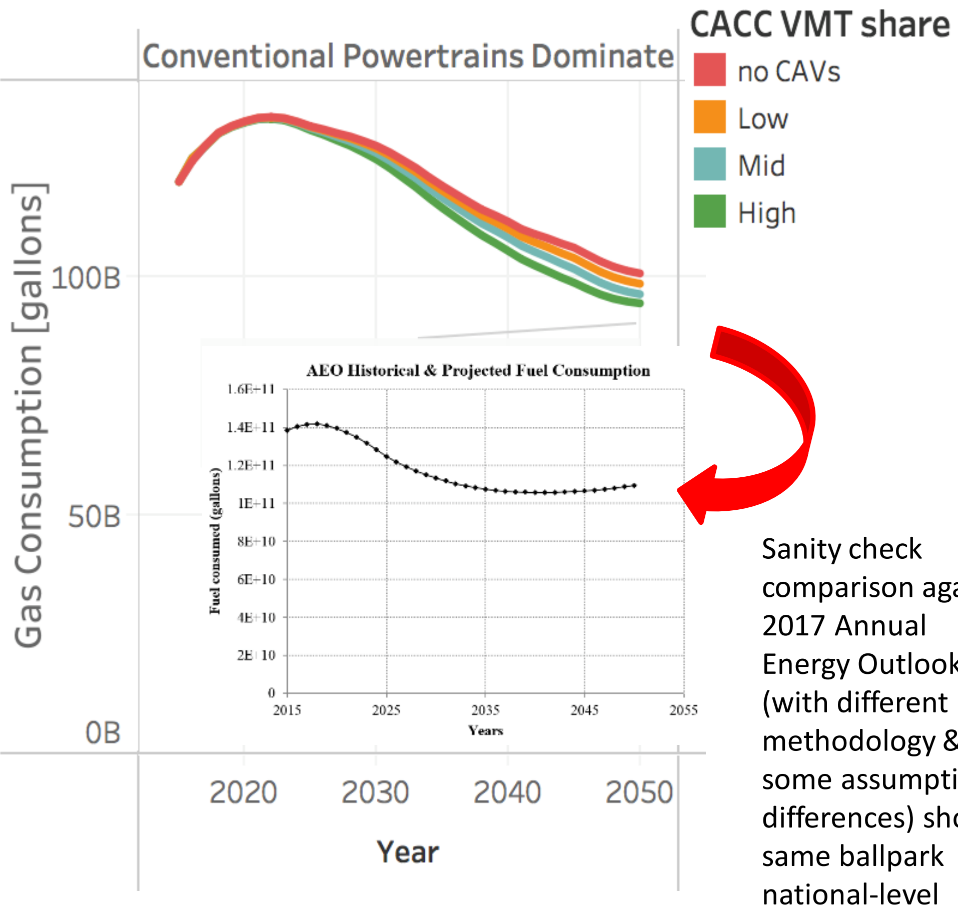


Chen, Y., Gonder, J., Young, S., and Wood, E., "Quantifying Autonomous Vehicles' National Fuel Consumption Impacts: A Data-Rich Approach," *Transportation Research Part A (2017)*, doi.org/10.1016/j.tra.2017.10.012.

Exercising the framework through hypothetical examples

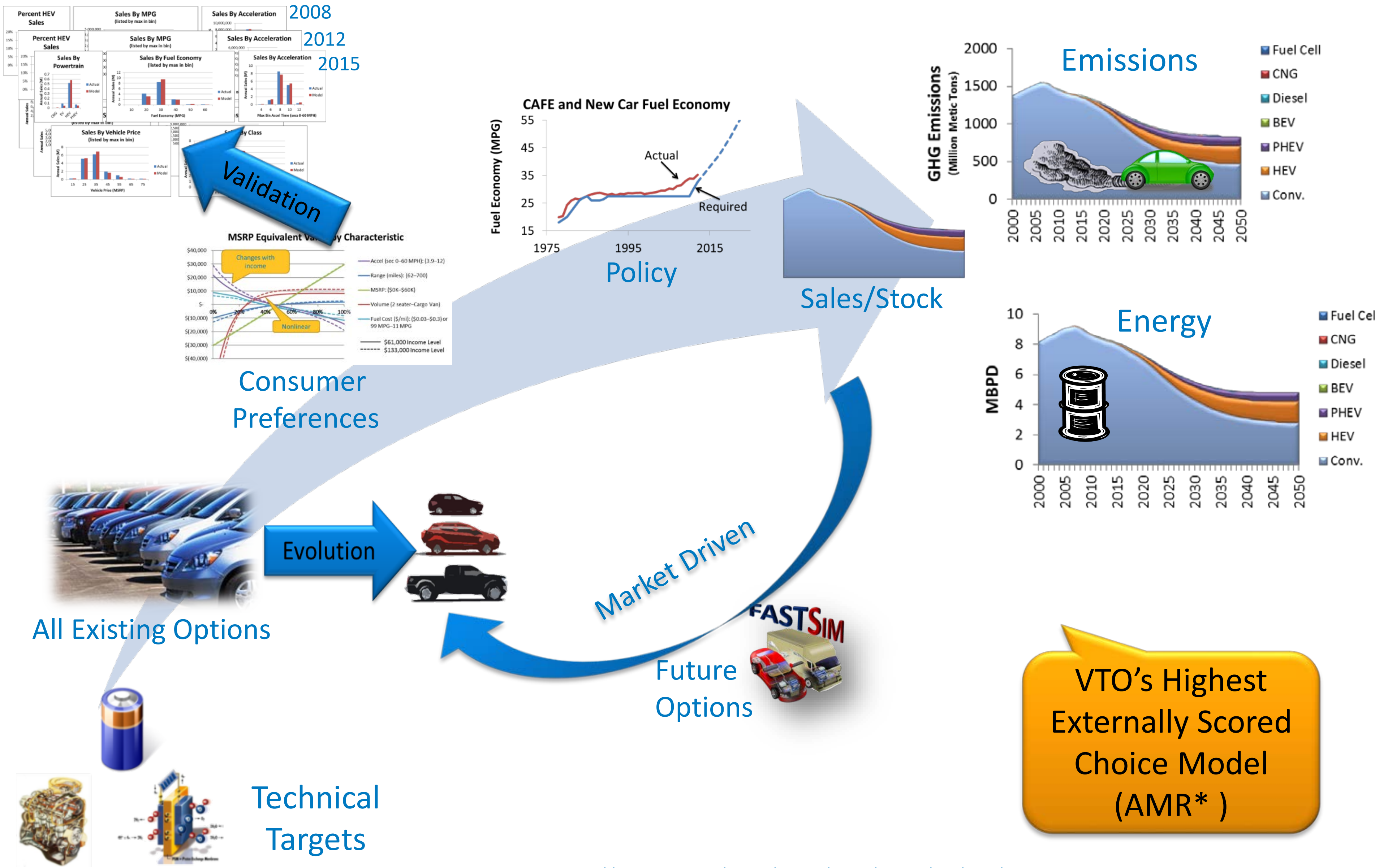
- While awaiting refined outputs from on-going work in other SMART Mobility tasks, applied preliminary/ placeholder inputs to the analysis framework, including from:
    - The Multi-Lab CAVs analysis report (Stephens, et al., 2016)
    - The LBNL-led CAVs concepts paper
    - Federal Highway Administration travel data
    - Potential future powertrain penetration scenarios
    - Educated guesses/placeholder values

Illustrative example for CACC penetration in a fleet that remains dominated by conventional vehicles



Sanity check comparison against 2017 Annual Energy Outlook (with different methodology & some assumption differences) shows same ballpark national-level baseline result

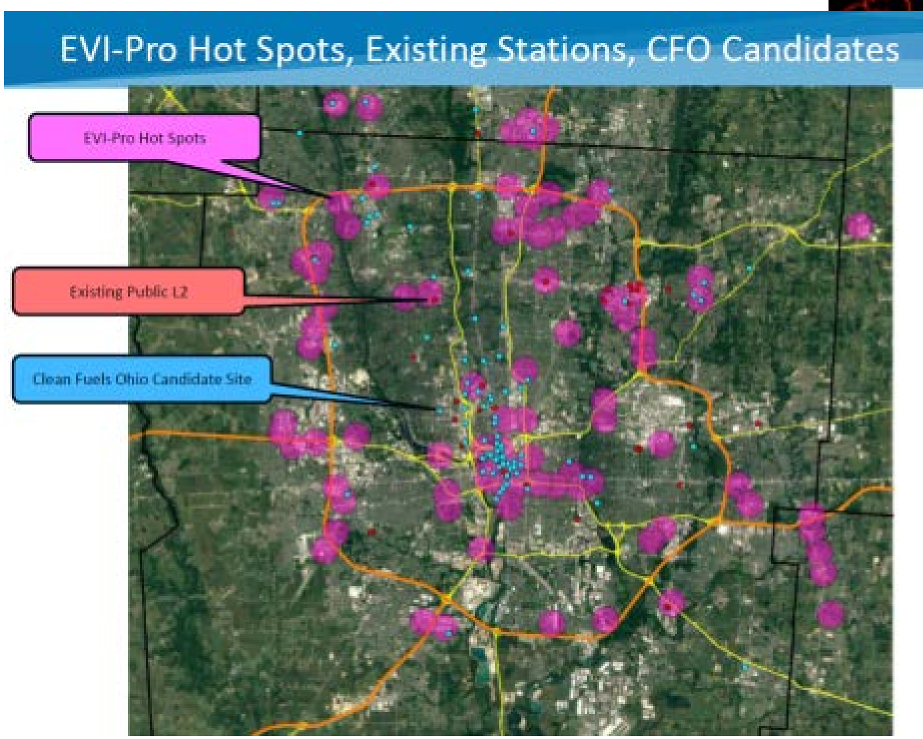
Automotive Deployment Options Projection Tool (ADOPT)



*https://energy.gov/sites/prod/files/2015/12/f27/09%20-%20Vehicle%20Analysis.pdf

EV Charging Infrastructure Analyses
From City- to National-Level; Applying EVI-Pro Tool

- 12 months INRIX GPS data
  - All trips intersecting Columbus region in 2016
  - 33M trips
  - 2.6B waypoints



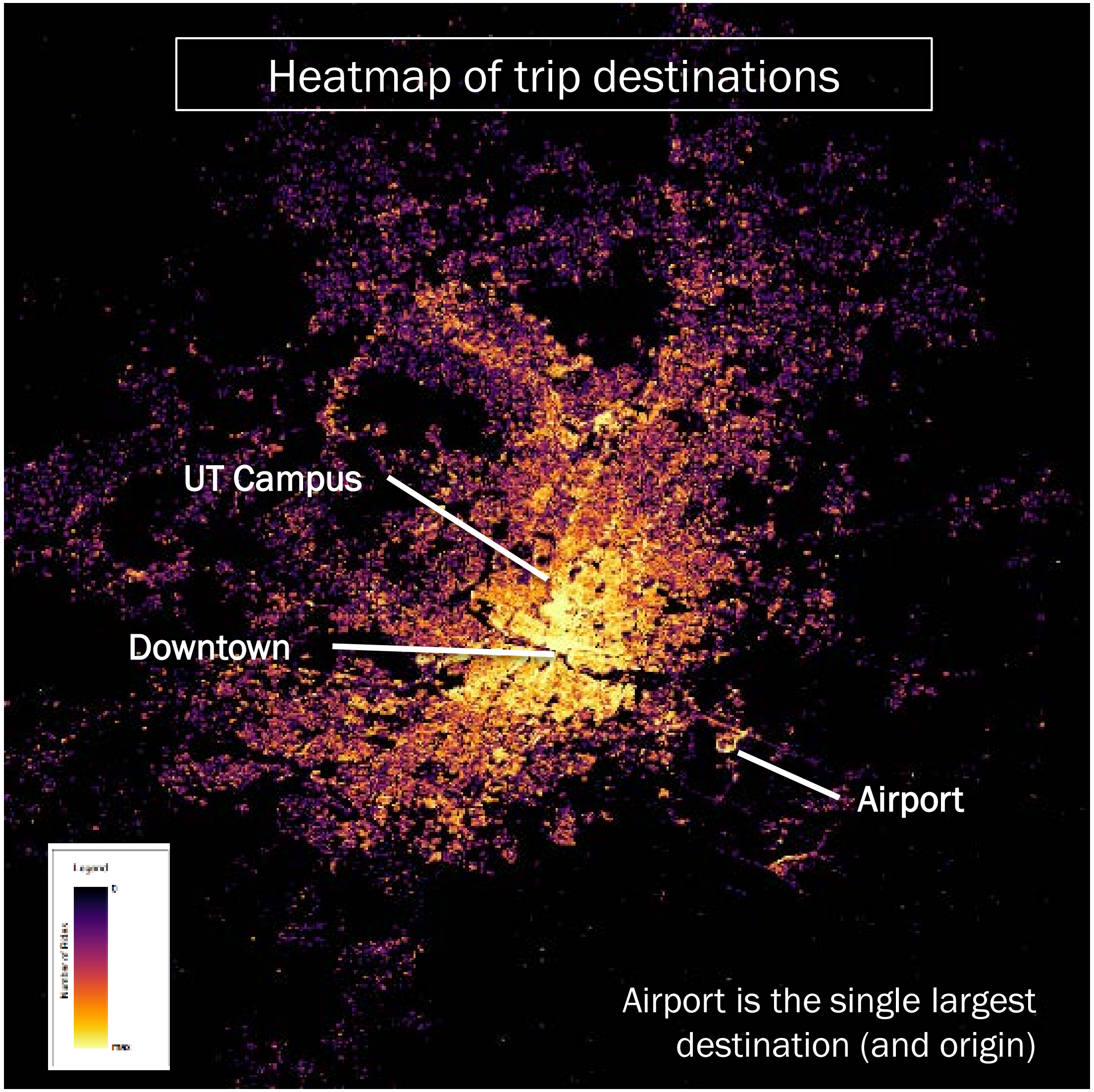
- Travel-data-informed infrastructure placement
- Comparison with existing /candidate infrastructure locations

Mobility as a Service/TNC Energy Analysis

Transportation Network Companies (TNCs) → Energy Impacts

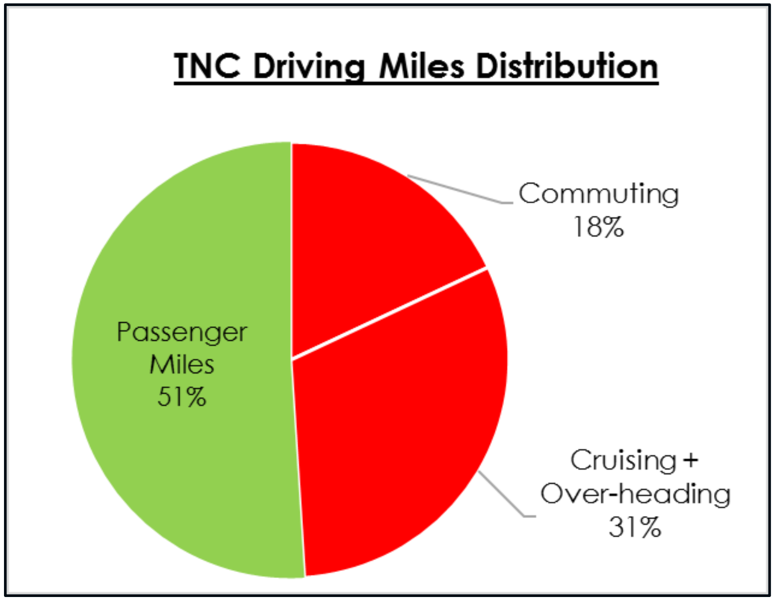
	TOPIC	SUB-TOPIC/RESEARCH QUESTIONS	POTENTIAL ENERGY IMPACTS	
Supplier (TNC)	**Vehicle Fleets**	Do TNC drivers use more fuel efficient/electric vehicles?	+	
		Is there an oversupply of vehicles?		−
	Deadheading	Deadheading percent of TNCs miles		
		Deadheading variation per driver strategy		−
		Deadheading variation per location		
Consumer (Passenger)	**Mobility Behavior Changes**	Vehicle ownership	+	
		Sharing: Vehicle occupancy and pooling	+	
		Mode replacement and modality style changes	+	−
		Induced travel		−
		Location	+	−
City	**Infrastructure**	Parking, density, multi-modal infrastructure	+	

Deadheading (RideAustin)



RideAustin data numbers

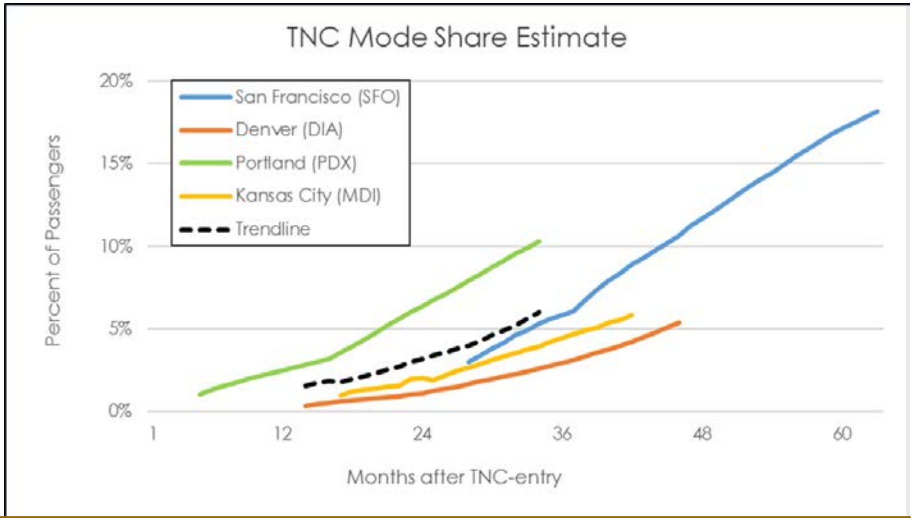
- Sample duration: 10 months
- Period: June 2016 to April 2017
- 4,961 unique drivers & vehicles
- 261,000 unique riders
- 1.5 million trips

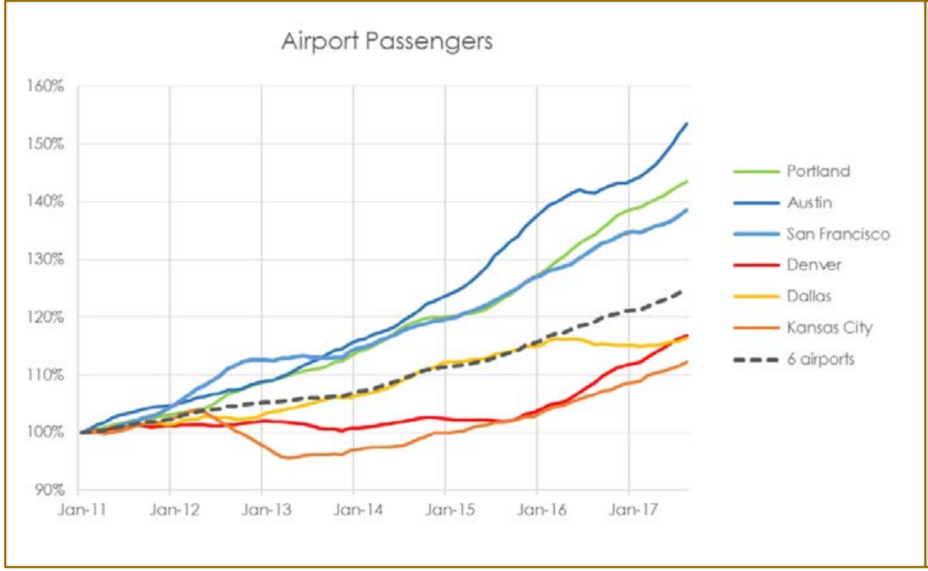


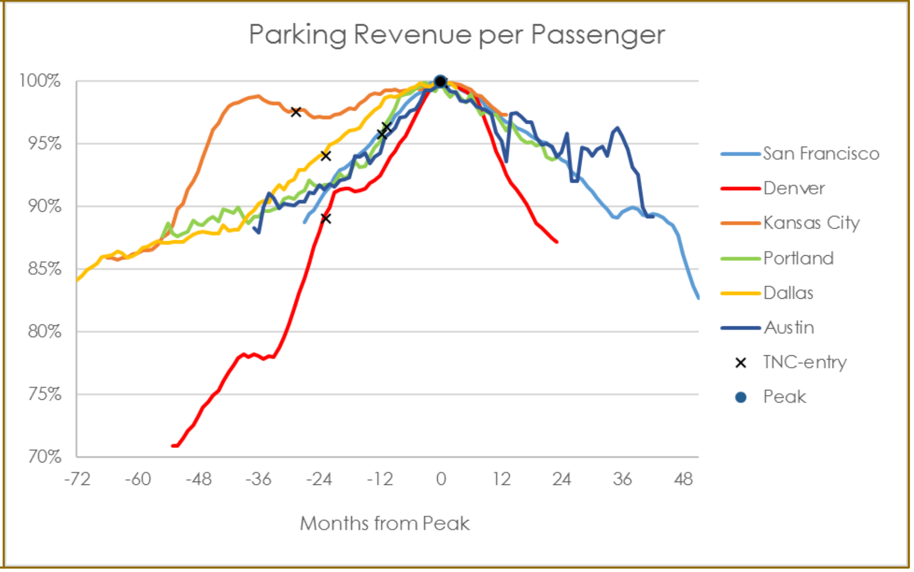
TNCs at Airports

TNC use and impacts:

- Data from public information request
- Air travel passengers have been rising
- TNC mode share estimates
- Change in ground transport revenues
- Mode shift: TNC, parking, car rental



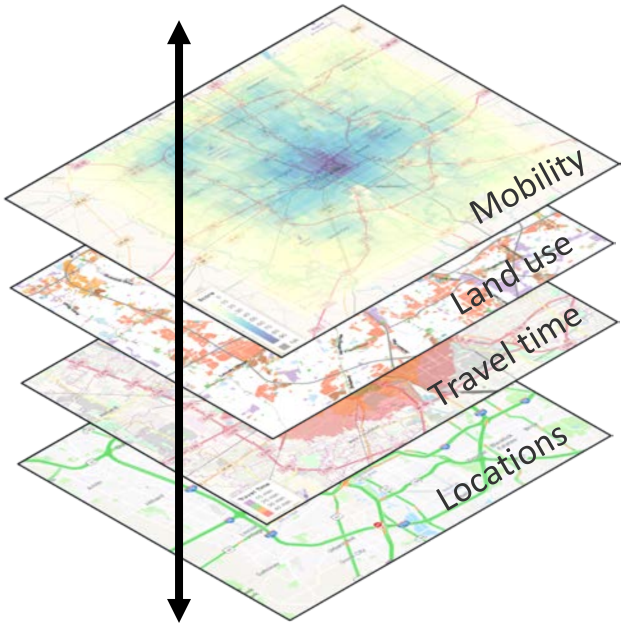




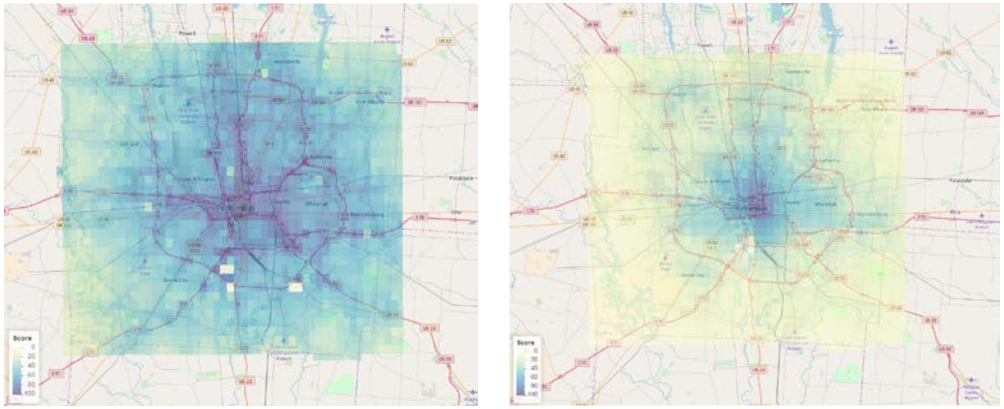
Mobility Energy Productivity (MEP) Metric

Quantify Mobility Benefits Relative to Energy Costs

- A first-of-its-kind, high-resolution, **comprehensive accessibility metric that considers energy dependency**.
- The **Mobility Energy Productivity (MEP)** Metric measures the fundamental quality of transportation networks to connect people with goods, services, and employment that define a high-quality of life.
- **Beta testing** carried out for **Columbus, OH.** Efforts underway to extend to other cities.



- Current research efforts focus on developing an easily adaptable methodology that various **SMART Mobility** research tasks can utilize to quantify the impact of technologies or strategies on the MEP of a region.



Driving

All Modes Except Driving

MEP Metric for Columbus, OH – Preliminary Analysis

Questions?

For more information:
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phone: 303.275.4462

NREL Transportation Research Website:

www.nrel.gov/transportation

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Initial testing to confirm customizability, flexibility, tractability, sensitivity and defensibility

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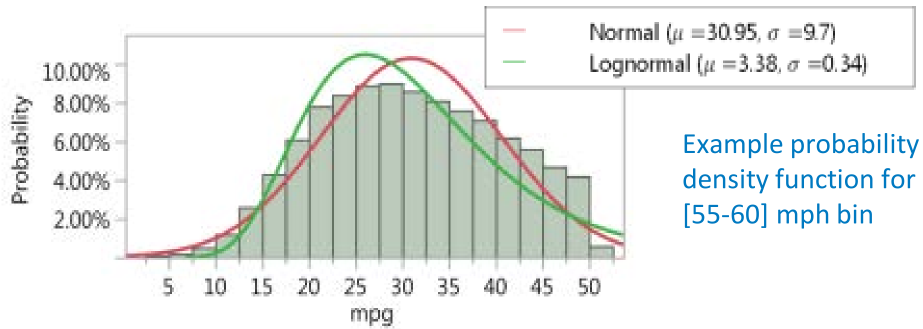

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Initial testing to confirm customizability, flexibility, tractability, sensitivity and defensibility

- Confirm tractability by ensuring FCR and VMT disaggregation can align; e.g.:

Conflation of typical daily VMT from the Highway Performance Monitoring System (HPMS) with typical daily speed profiles from TomTom data

Total VMT (in millions) distributed by road category, environment, and average driving speeds at the time of travel (considered indicative of congestion level)

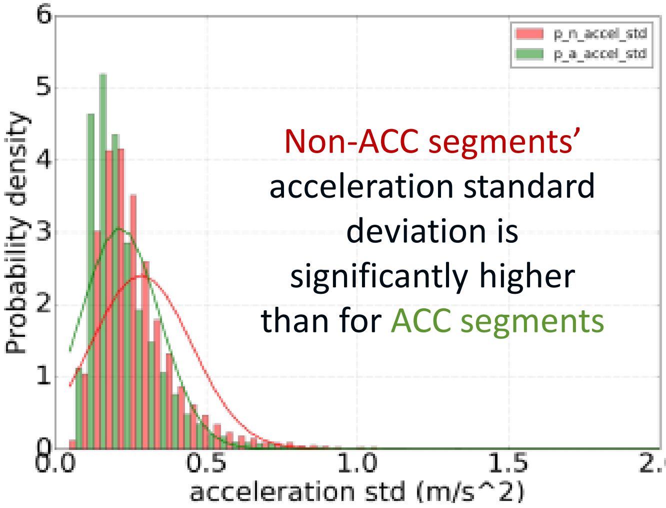
Total annual VMT of LDVs: 2.47 trillion
(based on aggregate HPMS dataset)

Avg Speed Bins (mph)	Freeways & Highways		Connectors & Arterials		Local Roads	
	Rural	Urban	Rural	Urban	Rural	Urban
[0-5]	0.000	0.000	0.004	0.020	0.013	0.123
(5-10]	0.006	0.046	0.148	1.123	0.350	3.147
(10-15]	0.019	0.172	1.267	8.469	3.290	17.752
(15-20]	0.040	0.375	3.553	22.210	5.324	34.868
(20-25]	0.092	0.679	7.287	43.720	5.992	33.297
(25-30]	0.183	1.466	13.926	74.978	9.742	38.947
(30-35]	0.339	3.160	23.217	114.512	13.668	48.795
(35-40]	0.466	5.173	30.301	129.852	14.877	47.928
(40-45]	0.668	11.947	36.814	116.873	15.699	30.652
(45-50]	0.951	24.784	45.680	84.444	12.975	12.415
(50-55]	1.863	52.048	58.591	54.800	12.835	4.803
(55-60]	4.956	114.023	95.089	50.712	12.506	1.868
(60-65]	16.907	207.692	67.158	55.630	2.516	0.332
(65-70]	62.286	186.095	62.429	34.555	0.080	0.001
(70-75]	95.927	42.591	8.523	2.249	0.000	0.000
(75-80]	4.802	0.328	0.002	0.000	0.000	0.000
>80	0.000	0.001	0.000	0.000	0.000	0.000
Total (from HPMS)	**189.50**	**650.58**	**453.99**	**794.15**	**109.87**	**274.93**

On-Road Data Analysis: Evaluating Automation Impacts on Vehicle Operation and Fuel Consumption

- Volvo Car Corp (VCC) provided NREL access to a large set of on-road vehicle operating data in adaptive cruise control (ACC) and manually driven (non-ACC) modes
- Developed methodology to assess ACC (partial automation) impacts, with intent to repeat on higher-level vehicle automation under *Drive Me*
- From the data NREL derived ≈17K segments (≤0.5 km in length) of ACC operation and ≈61K segments of non-ACC operation over the test route designated for *Drive Me*
- ACC segments showed (statistically significant) smoother overall driving
- Also examined ACC vs. non-ACC fuel consumption differences—found to vary with traffic speed and road grade.

Segments of contiguous ACC operation on the *Drive Me* test route



On-Road Data Analysis: Evaluating Automation Impacts on Vehicle Operation and Fuel Consumption

- In some conditions ACC fuel use >10% lower, in others no difference
- Calculated overall ACC impact by weighting the relative ACC vs. non-ACC fuel consumption rates in each driving condition by the amount of driving that occurs in each condition; **Overall: 5%-6% lower fuel consumption with ACC**

% Grade Bins

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

Applied methodology to estimate volume of travel in different speed and grade conditions experienced on the road network

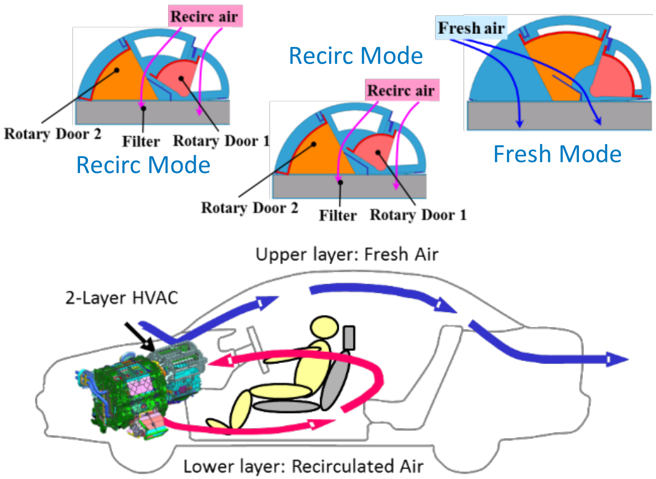
Potential next steps:

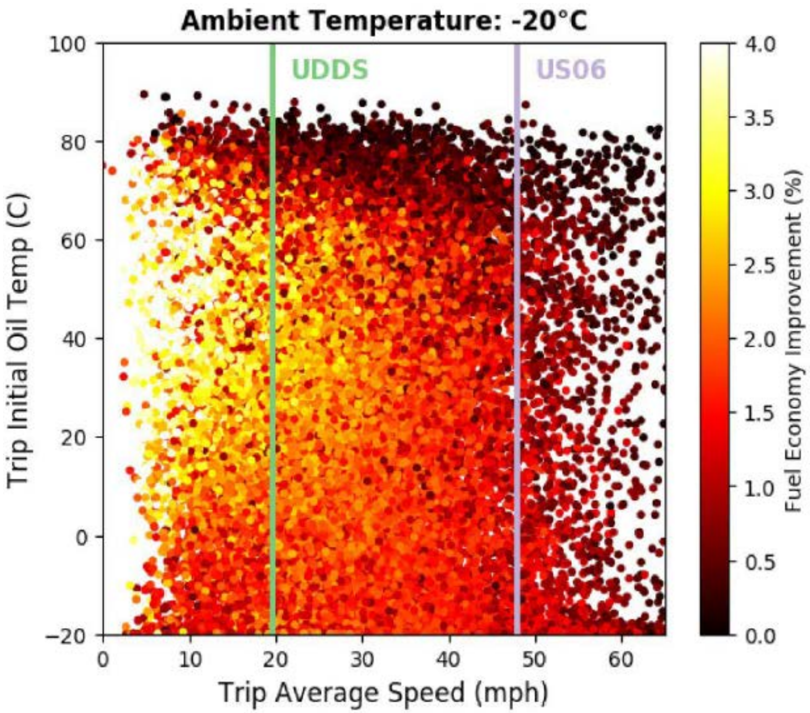
- Publish findings for partial automation (ACC) impacts
- Apply methodology to automated vehicle pilot under *Drive Me*
    - Data from customers using PHEV Volvo XC90s with higher-level automation

Applying Methodology to Quantify Real-World Benefit of Advanced Vehicle Climate Control Technology*

Approach

- NREL collaborated with ANL, Toyota, and Denso to test and model an HVAC technology





- An enhanced version of FASTSim was validated against ANL test data and simulated over representative real world driving conditions
- Over 200,000 trips from the Transportation Secure Data Center (TSDC) hosted by NREL revealed the conditions under which the technology provided the most benefit

* Published at 2018 SAE WCX

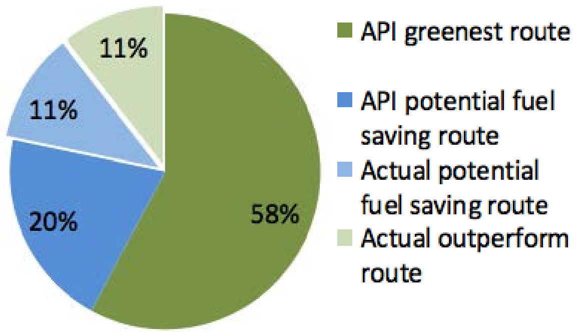
Significance & Impact

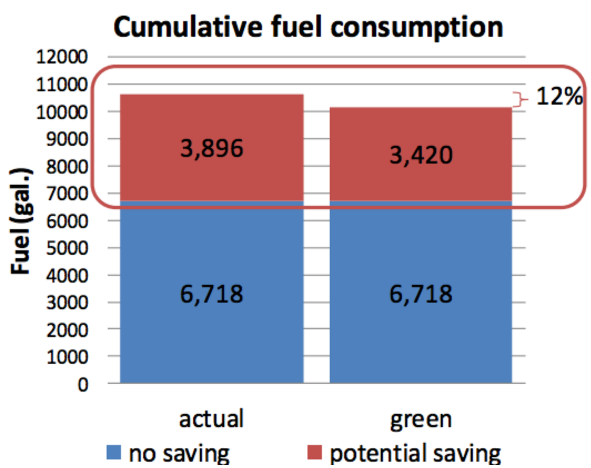
- NREL analysis revealed a real-world benefit of 0.18% per vehicle
  - Significant when deployed across Toyota's vehicle line
  - Toyota engineers to apply for off-cycle credit with EPA, present findings to internal Toyota Technical Congress
- Currently pursuing an additional off-cycle analysis projects

Green Routing Analysis

Preliminary Opportunity Assessment

- Applied a basic energy estimation model together with actual TSDC travel data and a routing API (i.e. Google Directions API)
- Assessed high-level opportunity for fuel savings from green routing
- Showed that 31% of all trips potentially have a less fuel consuming alternative
- For the dataset and estimation model used in this analysis, taking the "greener" route would have reduced fuel use by 12% (in that 31% subset of trips)
- Also found that 2/3 of the potential fuel savings come from routes that reduce both time and energy use



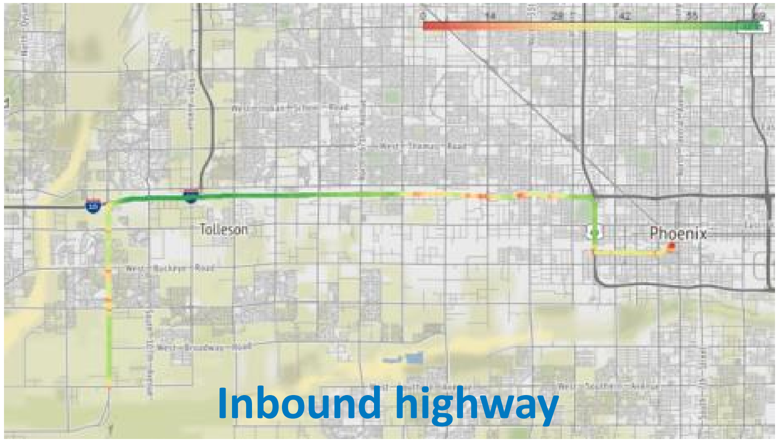


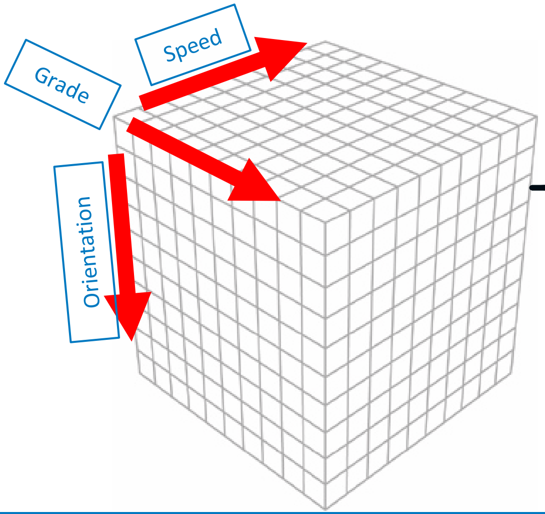
Zhu, L., Holden, J., Wood, E., and Gonder, J., "Green Routing Fuel Saving Opportunity Assessment: A Case Study Using Large-Scale Real-World Travel Data," Proceedings of the 2017 IEEE Intelligent Vehicles Symposium (IV'17), June 2017, Redondo Beach, CA.

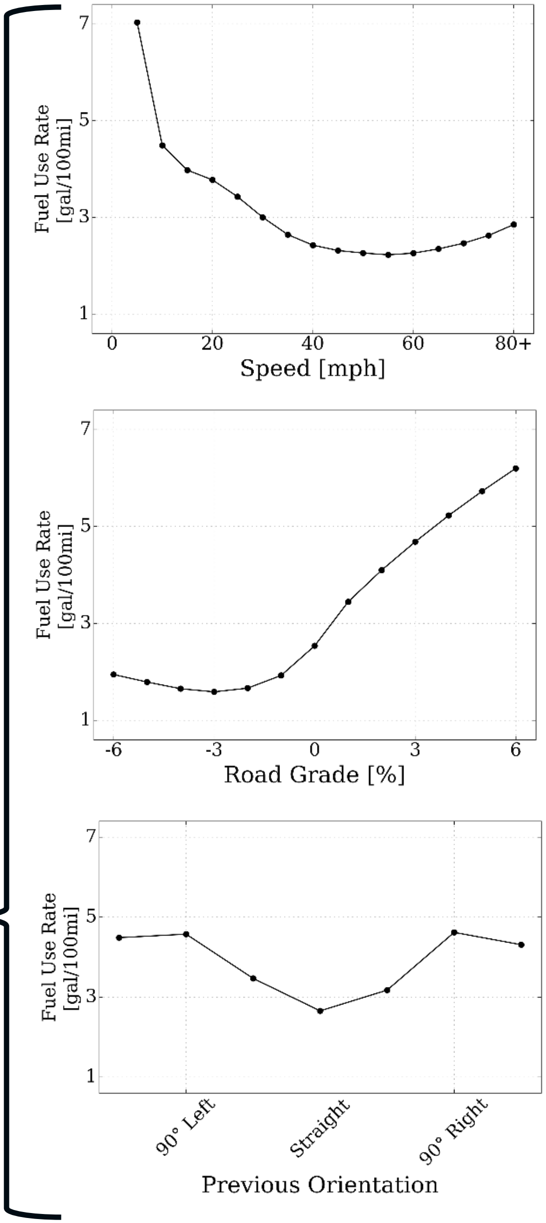
Green Routing Methodology Refinement & Validation

Energy Estimation Model Refinement & Validation

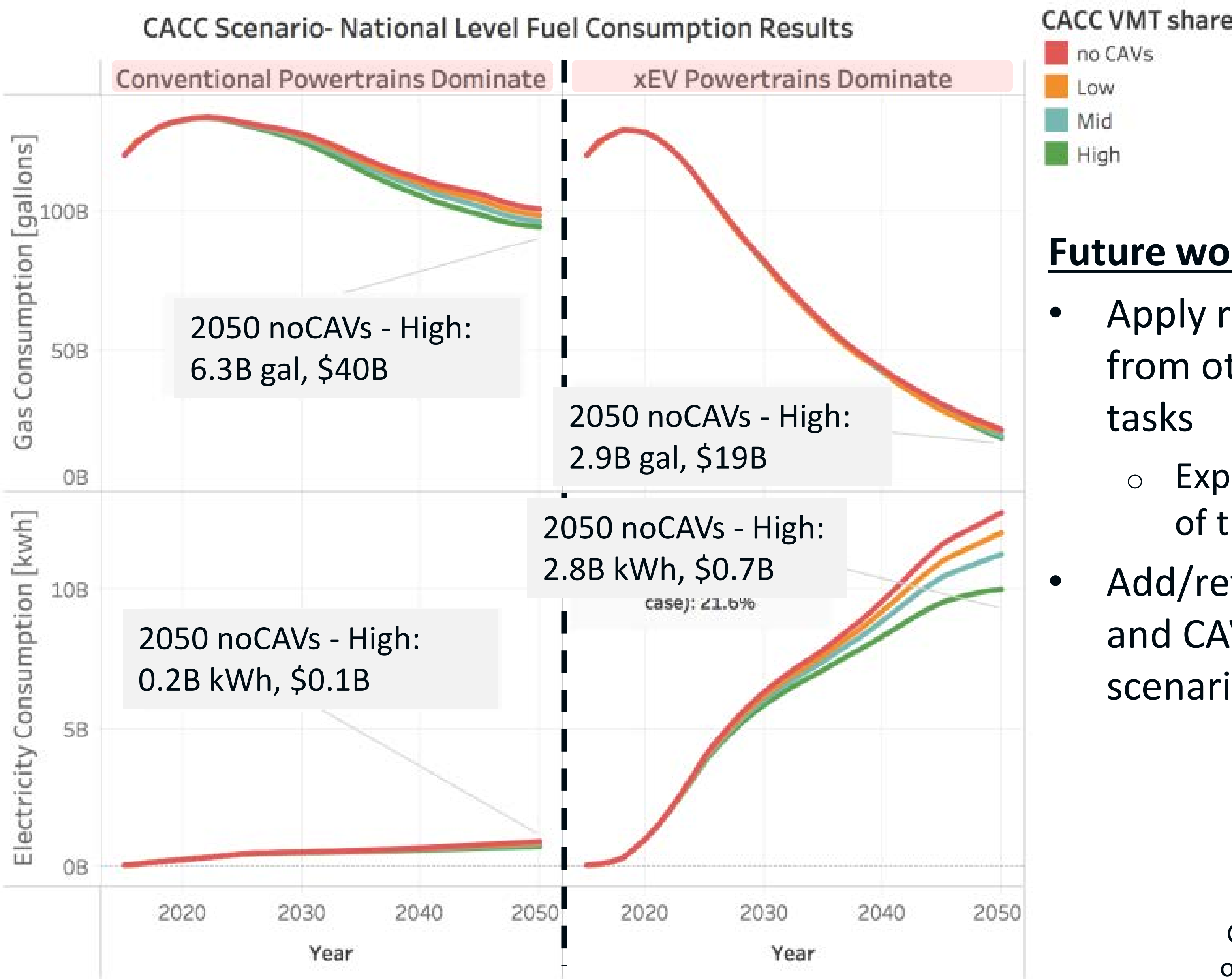
- INL collected data with multiple former AVTA vehicles over alternate routes
- NREL customized energy estimation model—sensitive to anticipated segment speeds, grades and turns
  - Trained by large-scale simulation of validated FASTSim model over TSDC drive cycles, then applied pre-trip
- Showed conventional vehicle energy estimation model correctly identified the greener route in all of the on-road tests







Illustrative Analysis Framework Results with Placeholder Inputs



Future work:

- Apply refined inputs from other SMART tasks
    - Explore sensitivities of the outputs
- Add/refine vehicle and CAV technology scenarios considered

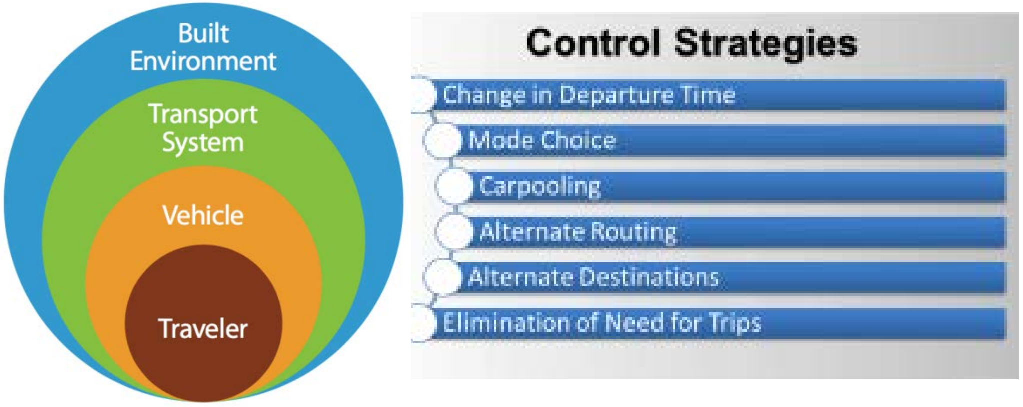
Cost comparisons based on AEO 2017 projections

ARPA-E TRANSNET: The Connected Traveler

Smart phone mobility app to encourage shifts in travel behavior toward energy efficient choices through incentives and improved convenience for the user

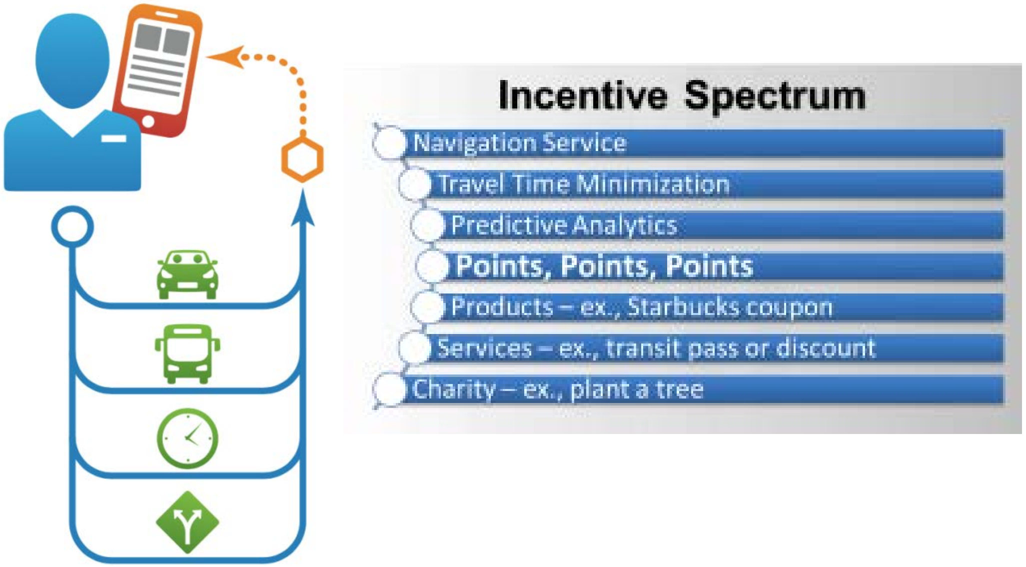
Improve existing transportation network and reduce energy use

- Travel time, mode choice, routing options



Mobility app leverages incentives to shift behavior

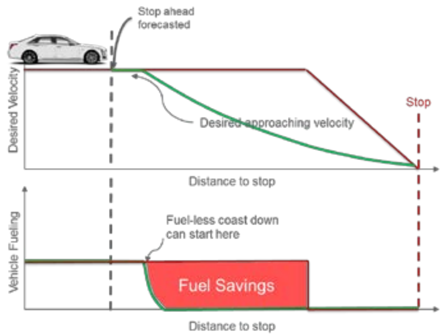
- Personalized via revealed choice data, user preferences
- Micro surveys build persona profiles of users



ARPA-E NEXTCAR Project with GM & CMU

"Info-Rich Vehicle Dynamics and Powertrain Controls"

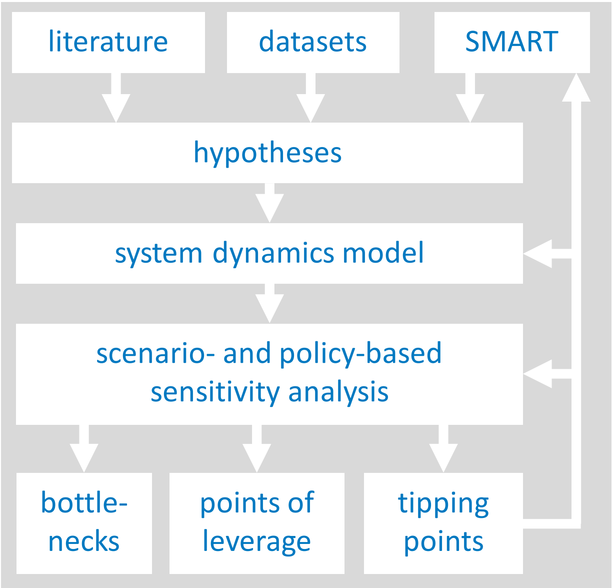
- Eco-Approach
  - Maximize the kinetic energy recovery through the use of preview information by coordinating vehicle speed control and various powertrain fuel-saving features (DFCO, AFM, gear selection, stop/start, etc.)
- Eco-Departure
  - Optimize vehicle departing acceleration profile and powertrain control calibration to maximize efficiency
- Eco-Cruise
  - Optimize powertrain operation to maximize efficiency based on look-ahead road grade and traffic conditions
- Eco-Routing
  - Select route that minimizes fuel consumption based on vehicle-specific powertrain characteristics without compromising travel time



GM = General Motors; CMU = Carnegie Mellon University
DFCO = deceleration fuel cut off; AFM = active fuel management

Other CAV Projects

- Modeling CAVs Transition Dynamics and Identifying Tipping Points
  - Identify and quantify circumstances/dynamics of potential transitions
  - System dynamics model-based examination of barriers, points of leverage, “tipping points” and “lock-in” for large-scale deployment of CAV technologies and Mobility as a Service



- Truck Platooning
  - Testing to measure interaction with aero changes and control enhancements
  - Truck activity data analysis to evaluate platooning opportunity space


Photo from Mike Lammert, NREL

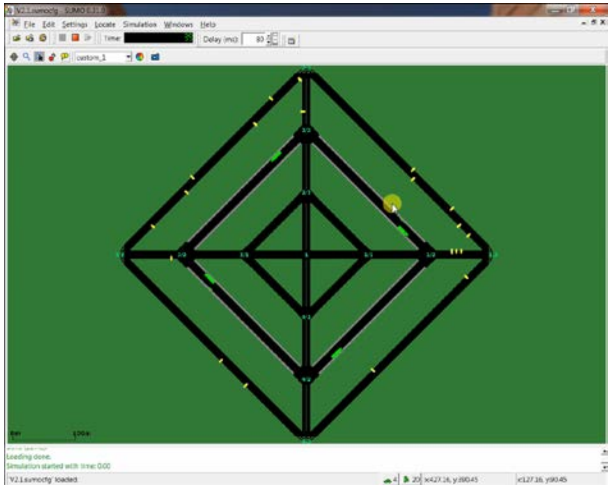
Automated Mobility Districts

Concept

- A new paradigm in which a **fleet of automated vehicles** displaces private automobiles for day-to-day travel is increasingly gaining attention and interest.
- Seeded by **preliminary exploration** of energy consequences using results from previous automated transit studies (**4-14% reduction** in fuel consumption).
- Developing an AMD modeling and **simulation toolkit** capable of quantifying the **energy and mobility benefits of AMDs**.
- The toolkit is based on **SUMO-** an open source traffic simulation package and integrates with **FASTSim**, a vehicle powertrain systems analysis tool developed at NREL.
- Collaborating with **real world AMD deployments** to obtain data (Greenville; Miramar etc.,)

Significance & Impact

- A generalized, open-source, and easy to use modeling toolkit to asses the energy and travel impacts of AMDs
- The toolkit will provide planning level models to estimate energy and mobility impacts across a number of different deployment scenarios.

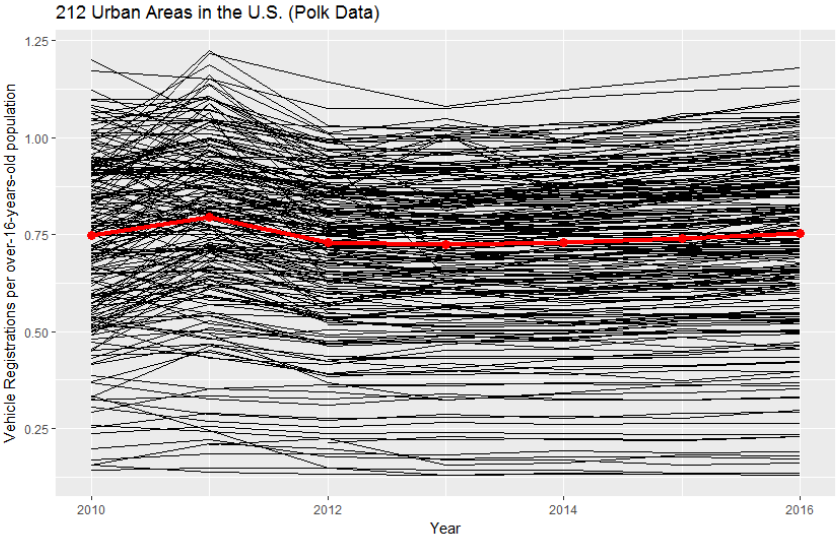


TNC Availability and Vehicle Registrations

Research Question: What is the impact of TNCs on vehicle ownership?
Regression analysis using a difference-in-difference (DiD) econometric model with vehicle registration (Polk) data, TNC-entry dates, and control variables

$$y_{st} = \boldsymbol{\beta}'\mathbf{x}_{st} + \boldsymbol{\alpha}'\mathbf{z}_{st} + \gamma_s + \delta_t + \varepsilon_{st}$$

y_{st}: dependent variables (vehicle registration per over-16-years-old population) for urban area s and year t:
$\mathbf{x}_{st}$: treatment effects (i.e., TNC entry date)
$\mathbf{z}_{st}$: controls (population density, income, children, etc.)
γ_s: fixed effect for urban area s
δ_t: fixed effect for year t
ε_{st}: unobserved error



Preliminary Results (212 urban Areas in the U.S.)

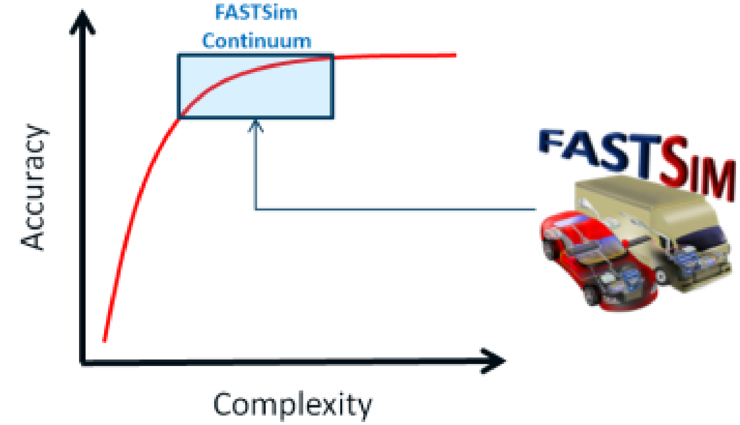
- Vehicle registrations, overall, do not change with TNC-availability
- Using an interaction for unemployment and TNC, the effect on unemployment changes; suggesting a possible decrease in vehicle registrations for general public, and increase for drivers
- Average "Vehicle Model Year" increase with TNC-availability; suggesting people are thinking twice before renewing a car

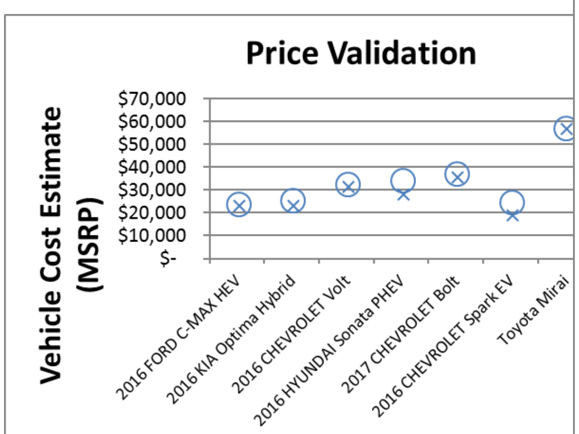
Transportation Secure Data Center (TSDC) – Value from detailed data, with privacy protections

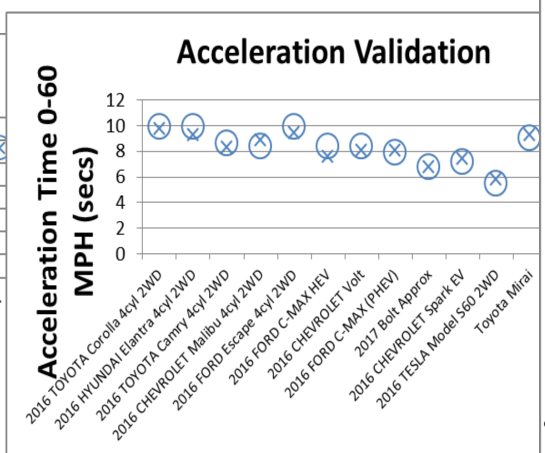
- High-resolution travel data (GPS points, trip ends)
- Cleansed/public download data
  - Streamlined access for cleansed data; helps limit accounts in secure portal to those with a legitimate need to work with the detailed data
  - Excludes latitude/longitude and other potentially identifying details (e.g., vehicle model)
  - Includes useful supplemental information (e.g., disaggregated travel distances)
  - Requires point-and-click user registration and usage agreement
- Secure portal for detailed/spatial data
  - Applicant & supervisor sign legal agreement
  - Analysis description form
  - Advisory group review
  - Virtual access (rather than requiring travel)
    - Data transfer prohibited
    - Use provided software
    - Aggregated results audited

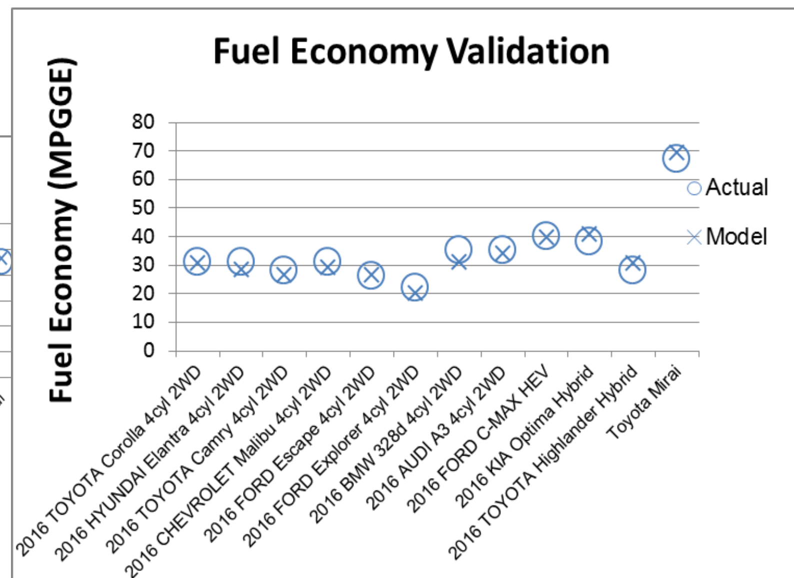
Vehicle Modeling in FASTSim

- **FASTSim's balance of accuracy vs. complexity**
  - Model captures most important factors influencing vehicle fuel economy, performance and cost
- **Well validated and widely accepted**
  - Simplest version with generic components gives good large-scale agreement
  - Complexity can be added to capture range of real-world considerations

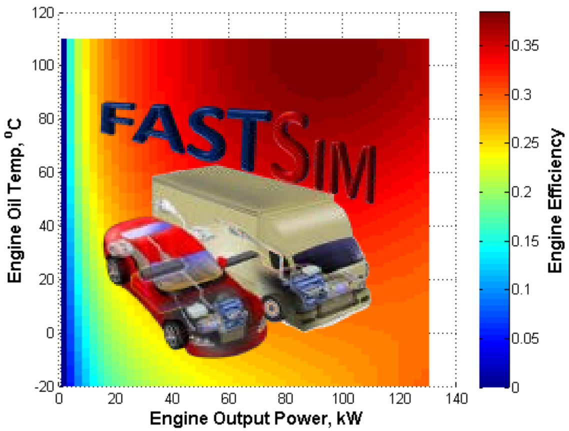




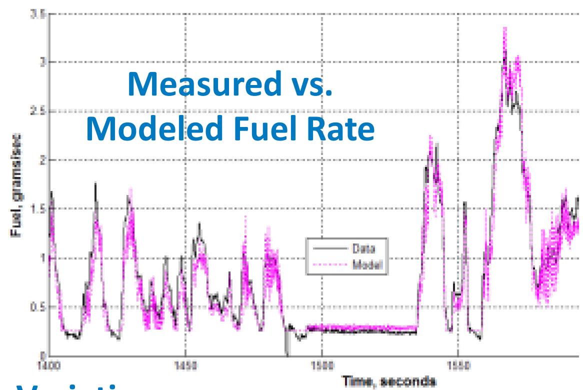


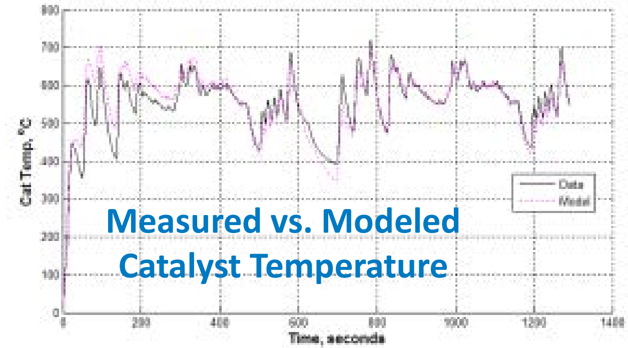


Real-World Fuel Economy Modeling

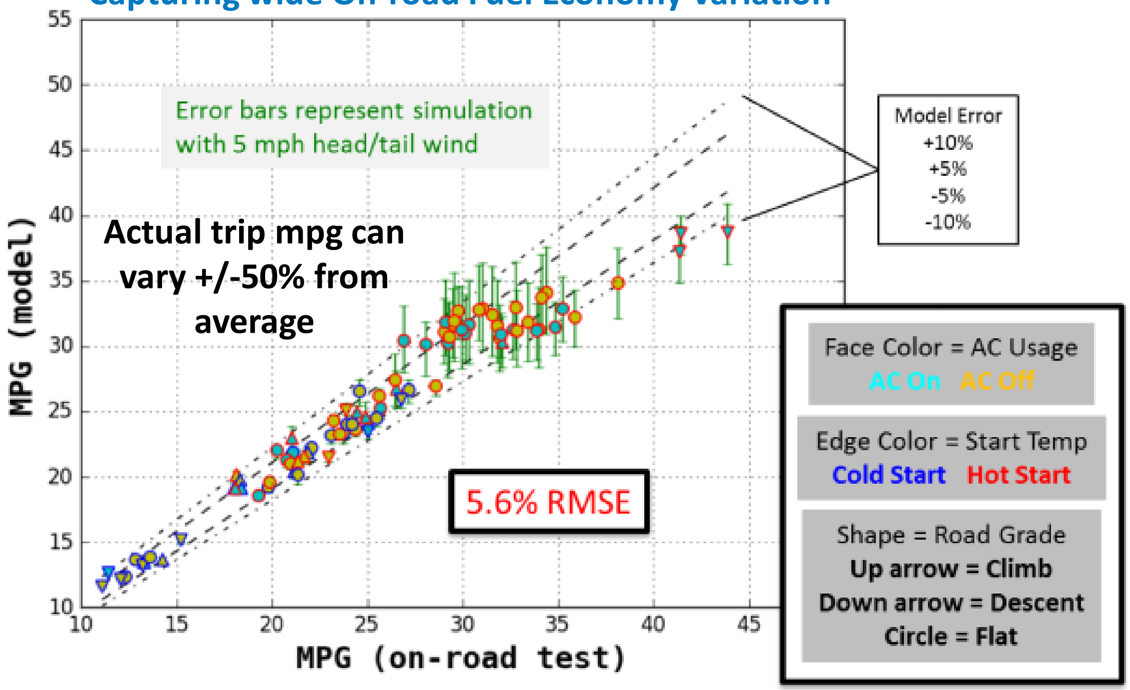


Example results for a conventional Ford Fusion:





Capturing wide On-road Fuel Economy Variation



Dyno Results (for reference)