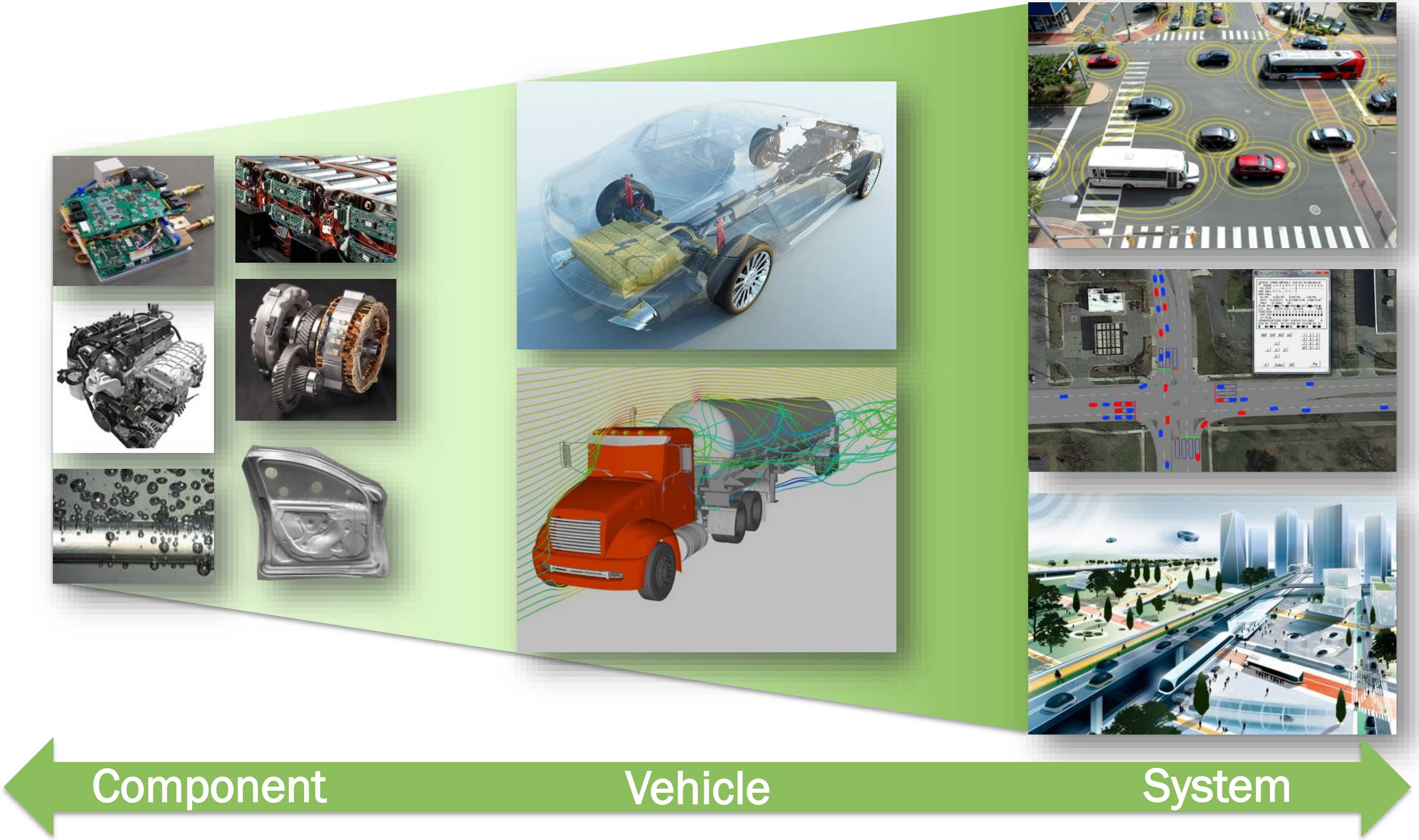
Energy Saving Through Connected and Automated Vehicles --what we learned at UM/Mcity

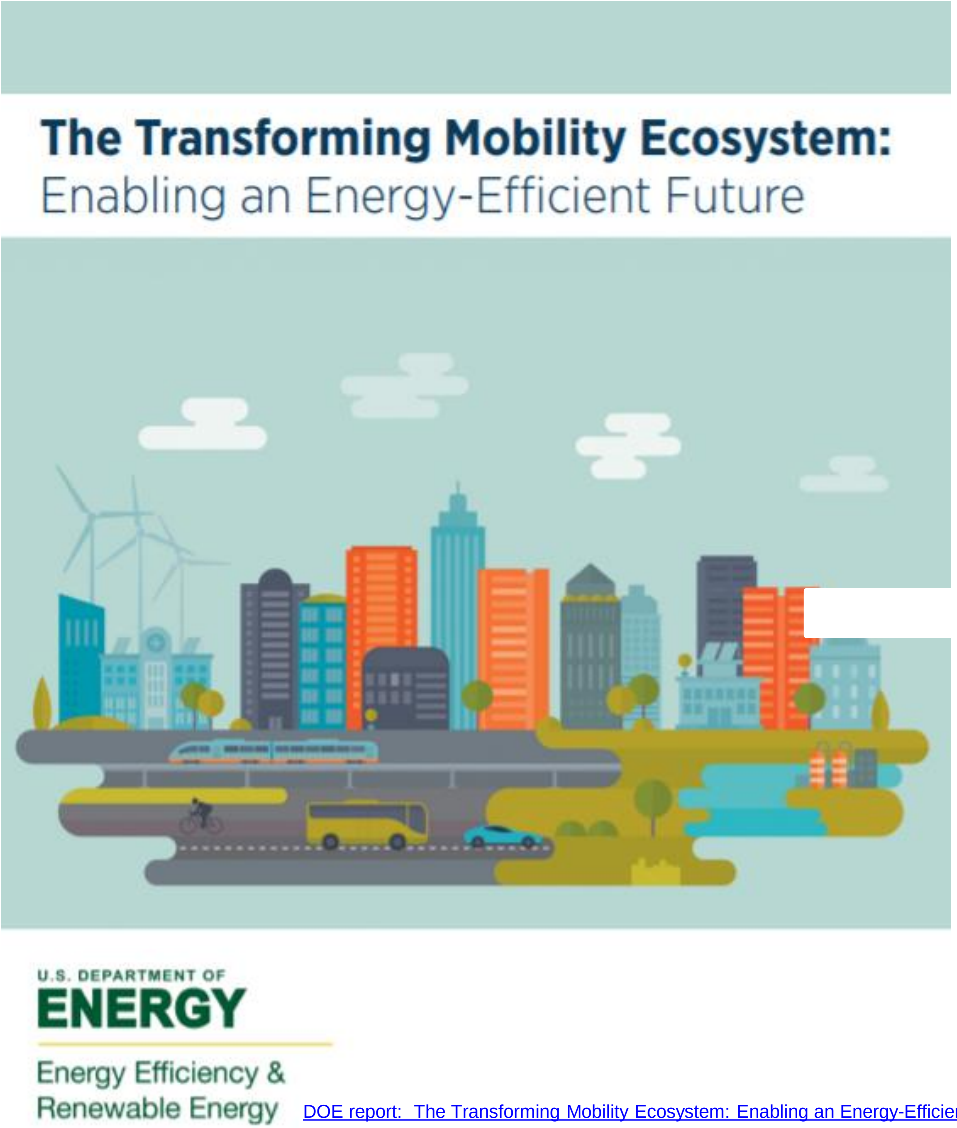
Huei Peng
Director, Mcity
Roger L. McCarthy Professor of Mechanical Engineering

CONDUCTING RESEARCH AT

ALL LEVELS



Uncertainties in Energy Impact of CAVs



DOE report: The Transforming Mobility Ecosystem: Enabling an Energy-Efficient Future

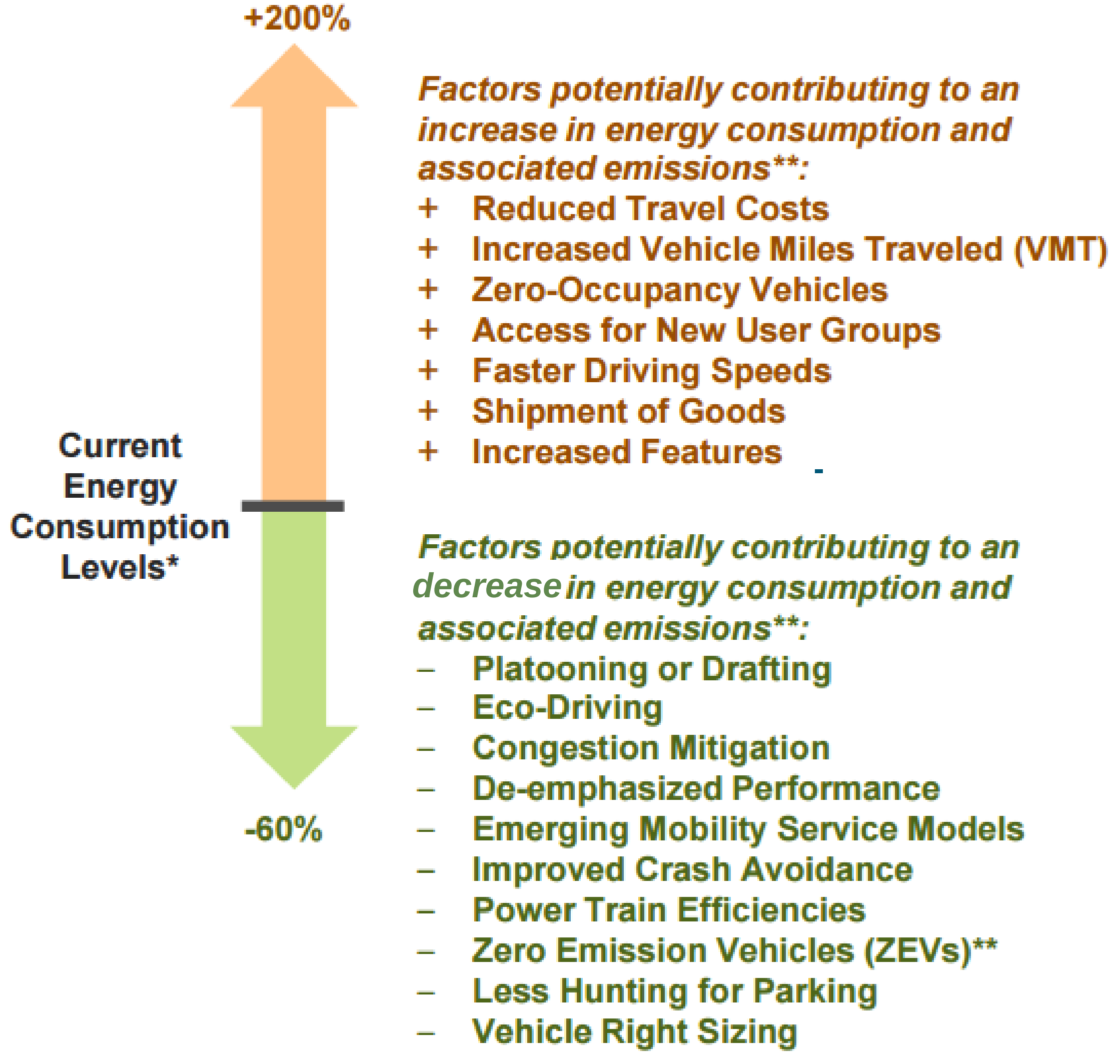
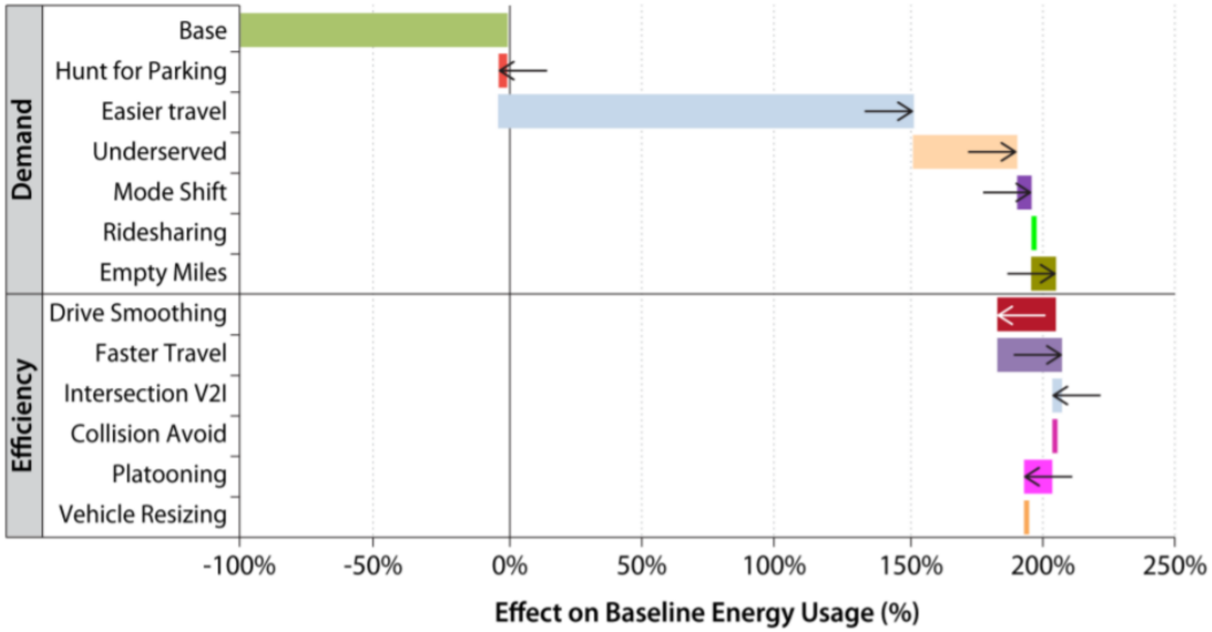


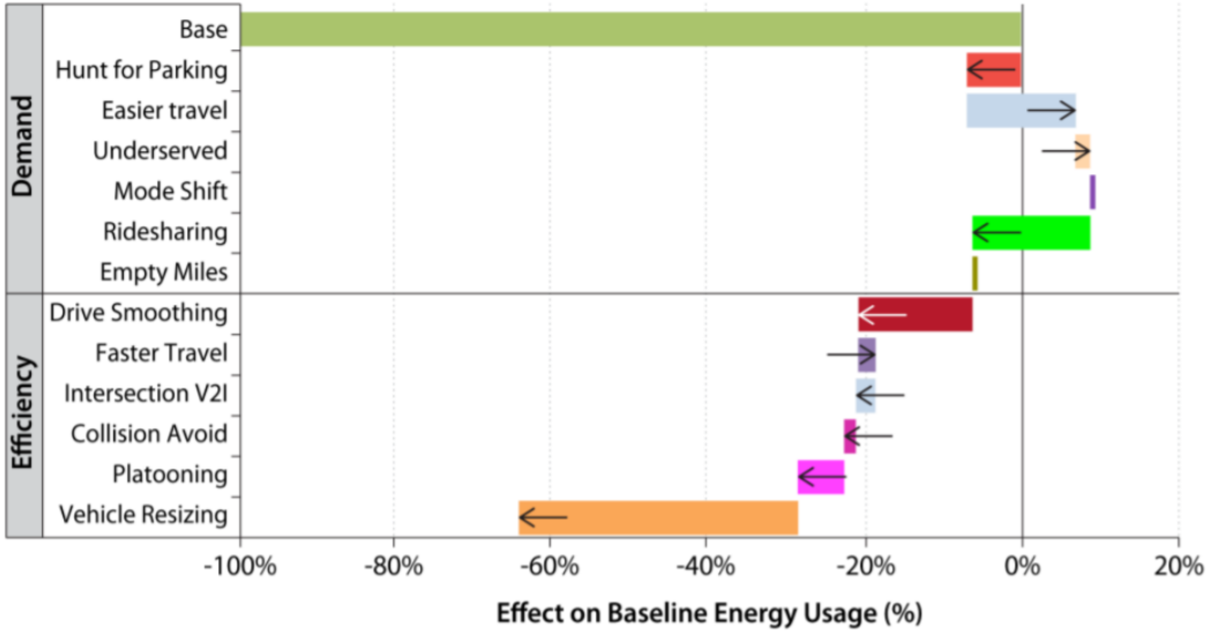
Figure 2. Energy Impacts of Connectivity and Automation

Influence on Fuel Use

Upper Bound

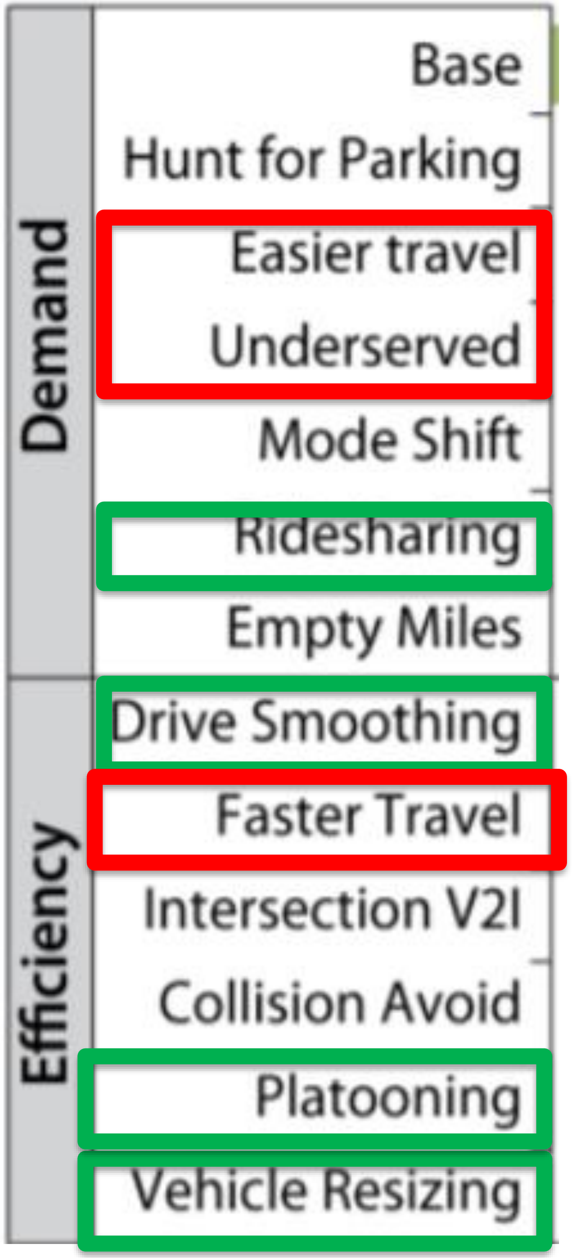


Lower Bound



What Did We Learn?

- Many factors
- Large uncertainties AND opportunities
- Important to
  - Develop the technologies,
  - Mitigate “problematic human behavior change”



Activities and Learning From Three Projects

- DOE EERE Incubator project

- ARPA-E NEXTCAR project (PI: Andreas Malikopoulos UD)

- Driverless shuttles at UM

DOE EERE Incubator project

Energy Implications of Connected and Automated Vehicles

PI: Huei Peng (UM)

Co-PI:
UM: Andre Boehman, Mark Gilbert, Dave LeBlanc, Henry Liu, James Sayer
ANL: Josh Auld, Erik Rask, Aymeric Rousseau, Ann Schlenker
INL: John Smart

Data

Task 1
Fleet testing

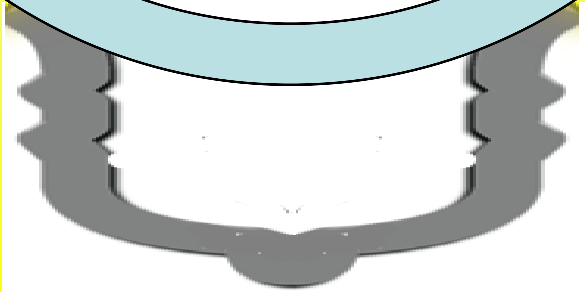
Task 4
Simulations

Task 5
Adaptive
Traffic
Signals

Energy impacts of CAVs

Simulation

Testing



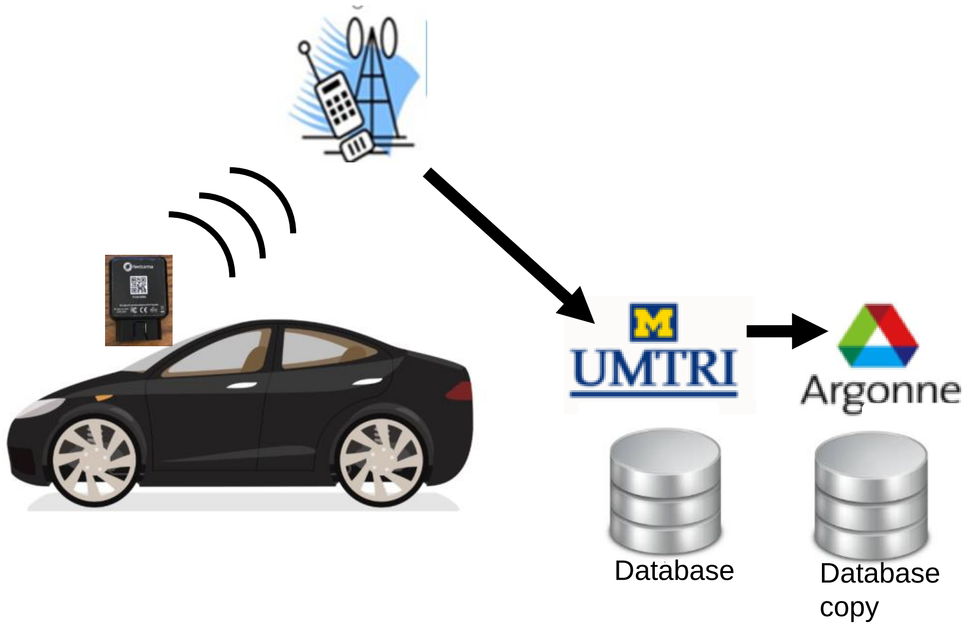
Task 3
Traveler model

Task 2
Driver behavior

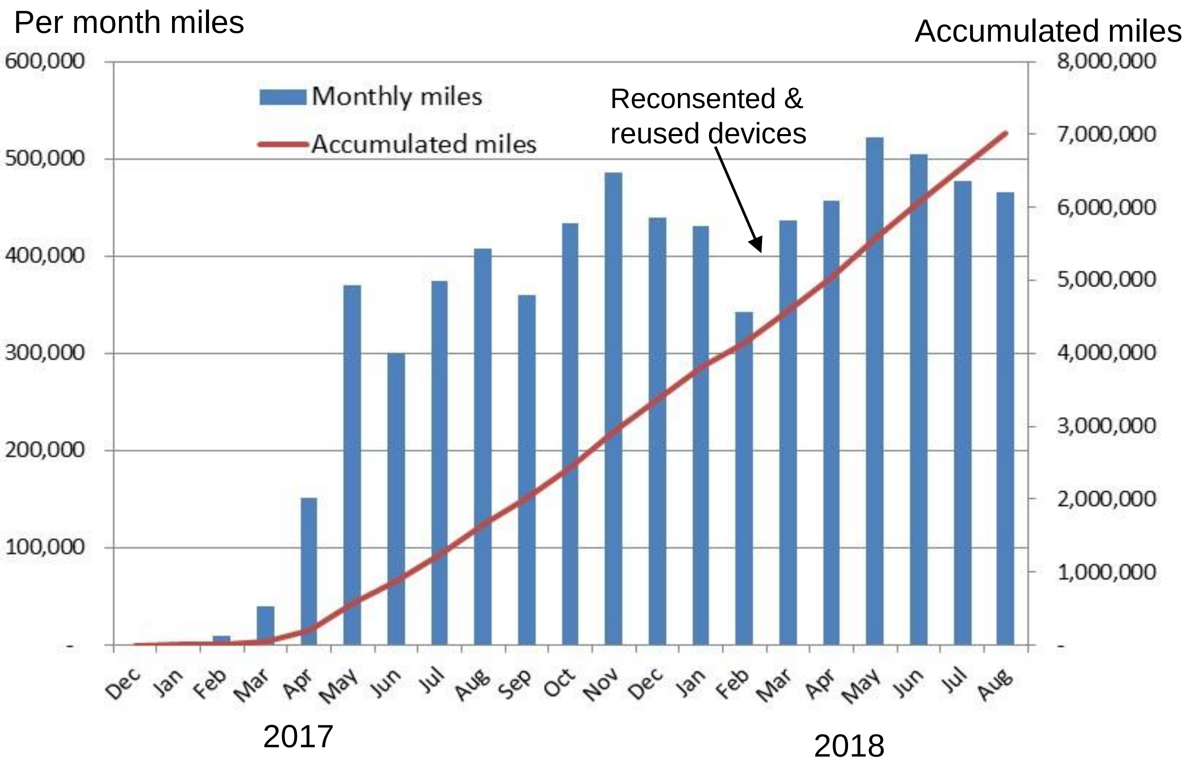
Major Work/Outcome

- Collected energy consumption data + GPS from ~500 vehicles
- A calibrated Ann Arbor model in Polaris (ANL)
- Eco-Routing in Ann Arbor
- Human behavior model (How they follow advises from CAV functions?)
- Human driver etiquette
- Adaptive Traffic Signal Control Algorithm

Data Collection (500 vehicles, 8 million miles)



Powertrain type	Number of vehicles(09/10/18)
ICE & HV	300 (91.7%)
PHEV & EV	27 (25 PHEV, 2 EV) (8.3%)
Total	327



Updated on 09/10/18 :

- 739,535 trips with nonzero travel
- 7,127,289 miles in total
- **8.1 million miles** – projected total mileage for project (device cellular plans expire 11/10/18)

Calibrated Ann Arbor model in Polaris (ANL)

Example: Vehicle ID 247 and Trip ID 215

Vehicle Instance

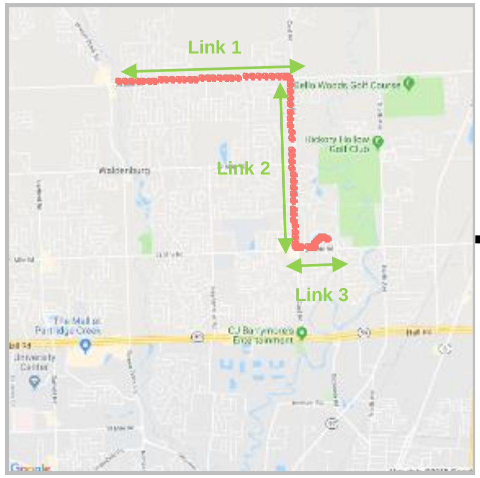
Assign

Powertrain Type
Engine Type
Transmission Type
Number of gears
Engine Power
Drag Coefficient
Rolling resistance
Vehicle Weight
Vehicle Performance
…

Extract

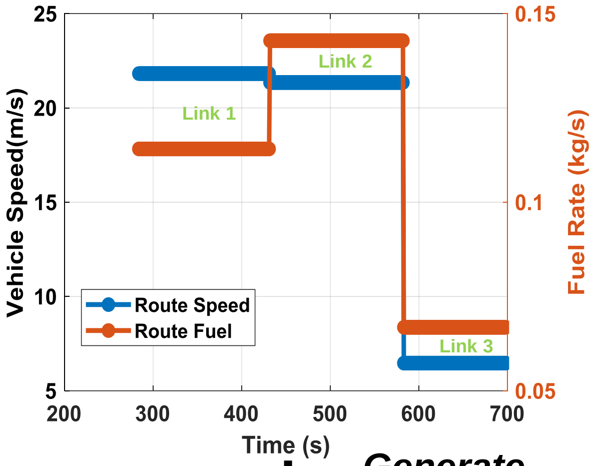
Time
Vehicle Speed
Fuel consumed
GPS position (lon/lat)

Map Matching



Process route data

(POLARIS "like")



Generate route like features

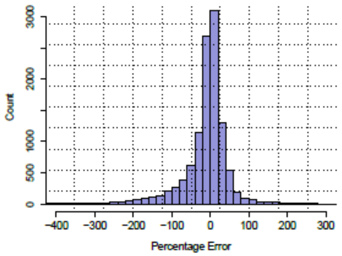
Distance covered
Length Link
Time traveled on Link
Time stop on Link
Average Speed on Link
Speed Limit of Link
Distance covered previous link
Distance covered next link
Average Speed previous link
Average Speed next link
Speed Difference previous link
Speed Difference next link
Traffic load
…

Data wrangling
Outlier detection

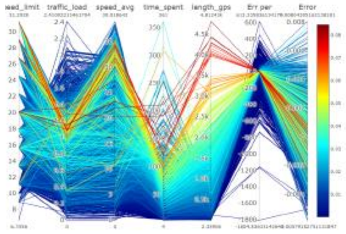
Model

$$y_0 = f_0\left(\sum_{h_2} w_{h_2 0} f_{h_2}\left(\sum_{h_1} w_{h_1 h_2} f_{h_1}\left(\sum_{i} w_i x_i\right)\right)\right)$$

Prediction

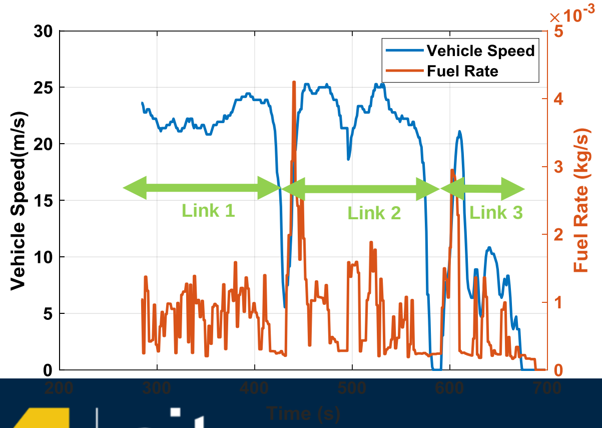


Error Circulation Analysis

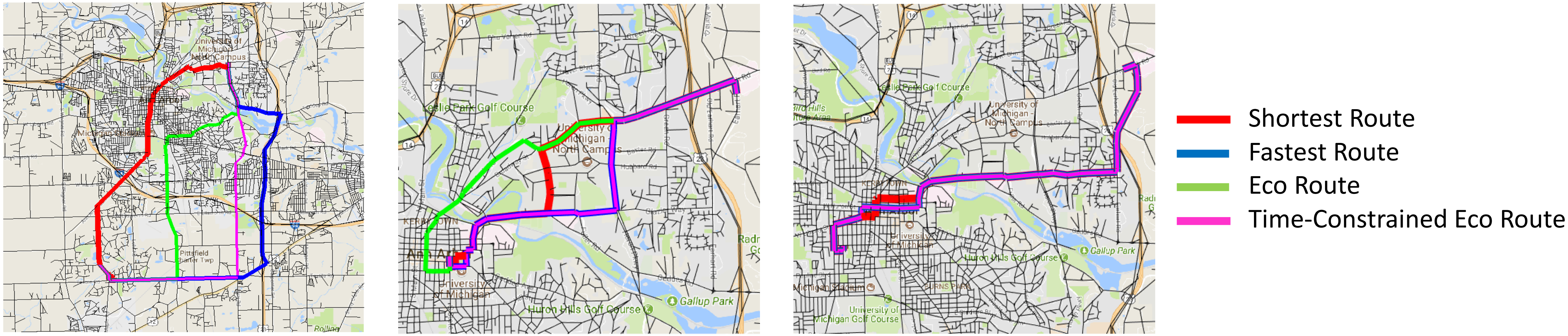


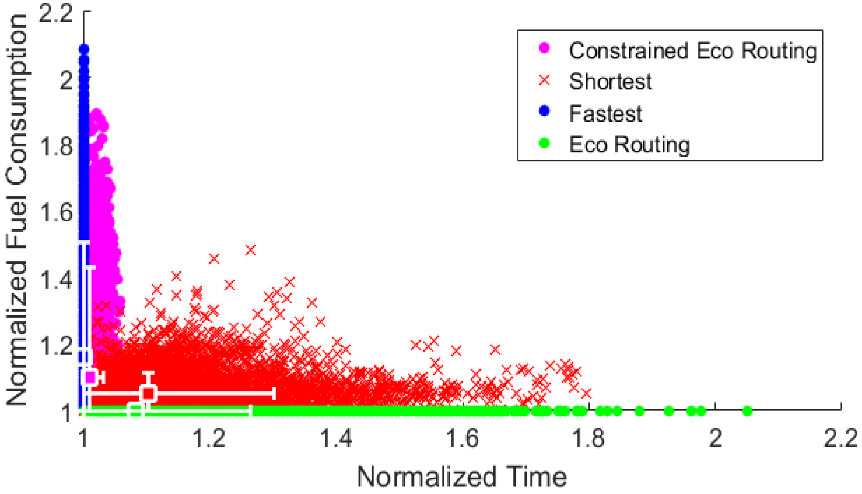
Cross-Validation

(different data sets)



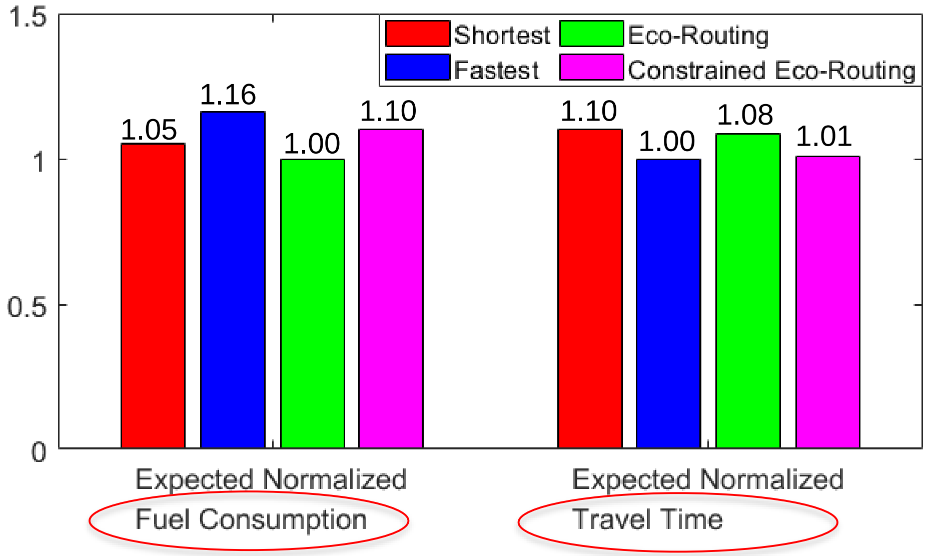
Eco-Routing for Ann Arbor (fuel ↓6%, time ↑1%)





$$fc_{normal} = \frac{fc}{fc_{Eco-Routing}}$$

$$t_{normal} = \frac{t}{t_{Fastest}}$$



How human drivers follow advises from CAV functions?

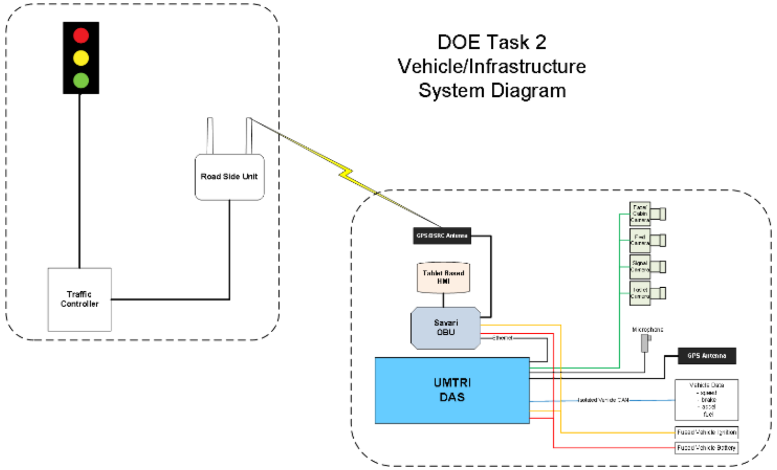
– Experiment conducted at MCity

- 32 participants
- 16 younger (between 20 and 30 years old) and 16 middle-aged (between 40 and 50 years old)
- Some college or lower (19%), bachelor’s degree (47%), master’s degree or higher (34%)

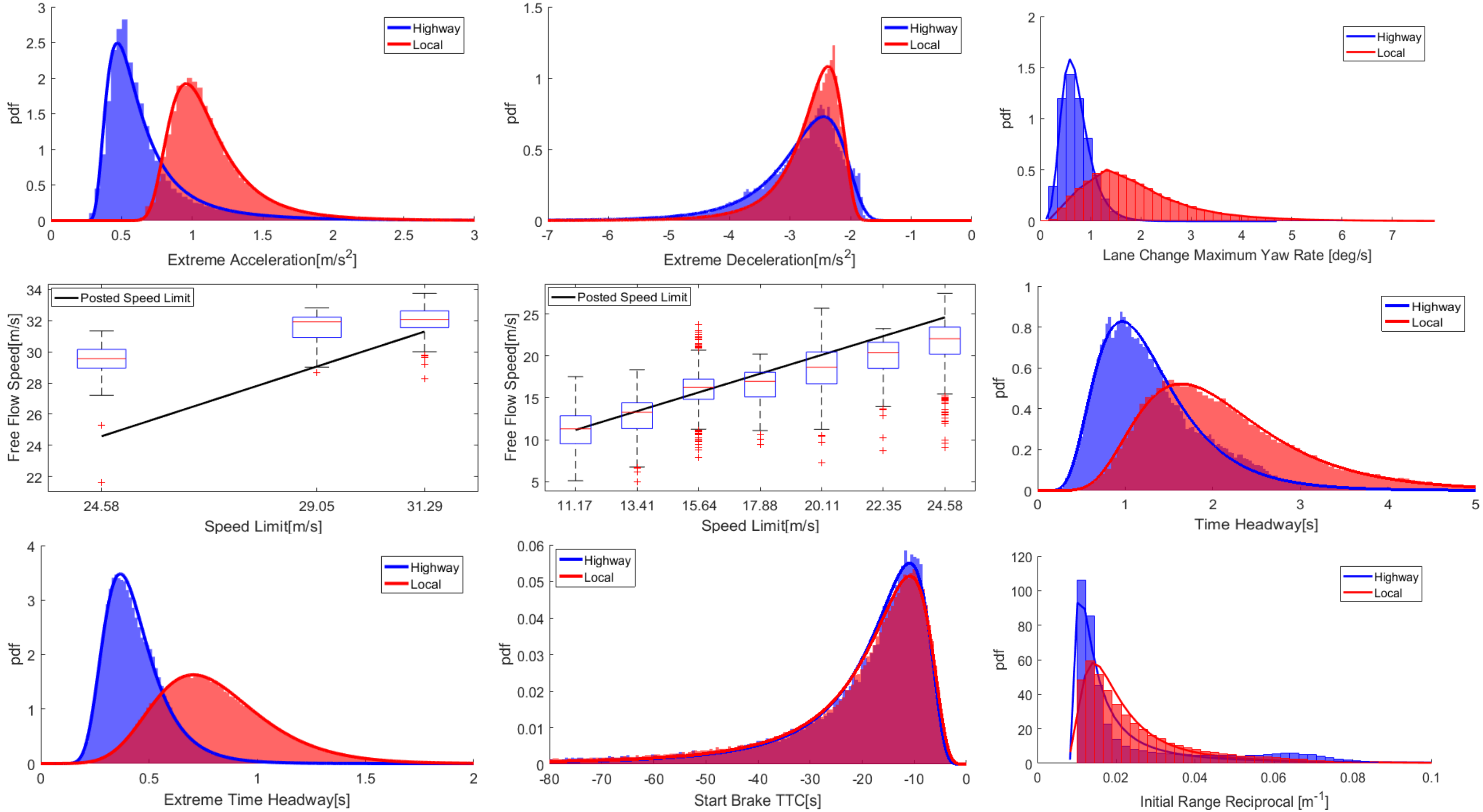
– Vehicle instrumentation

- Honda research vehicle
- Four cameras (front view ,driver face ,over the shoulder, and rear view)
- DAS, GPS and HMI tablet

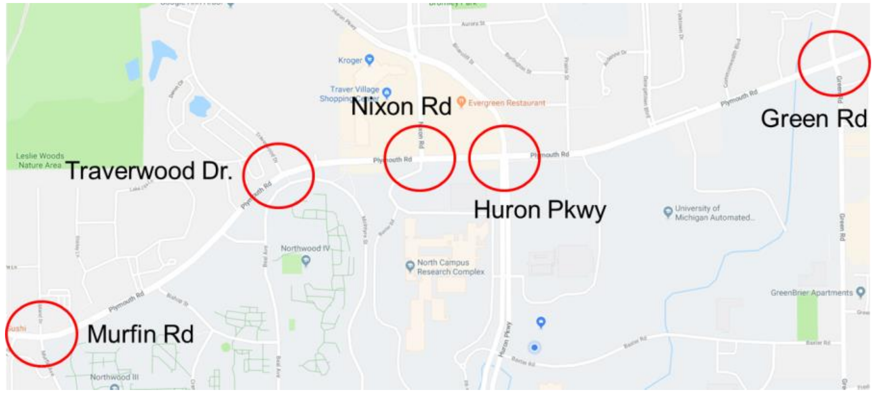


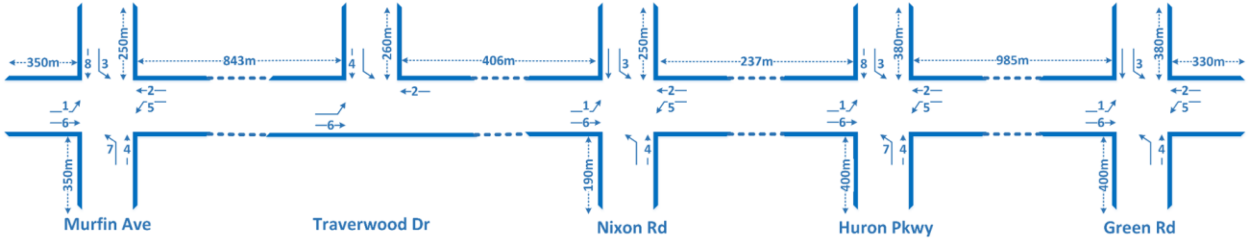
Human Driver Etiquette

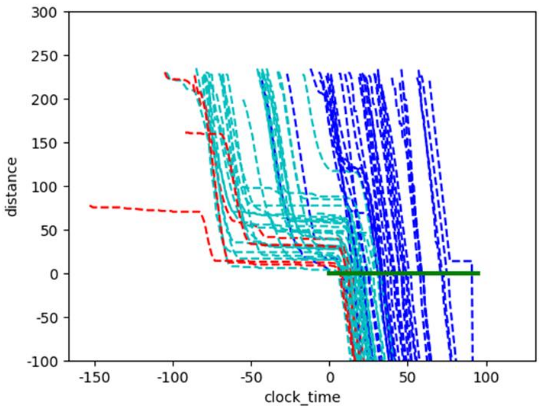


Adaptive Traffic Signal Control Algorithm

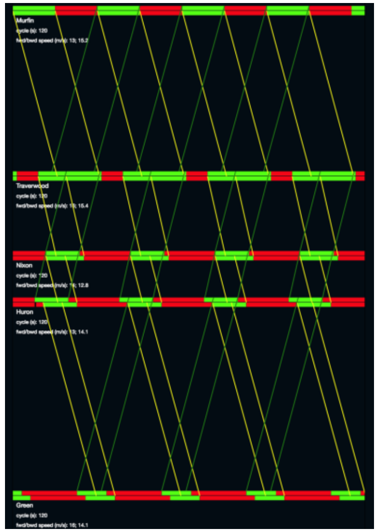


abstraction





Example field data



Optimization to reduce delay

Intersection	ID	Start	Duration	ID	Start	Duration	ID	Start	Duration	ID	Start	Duration
Murfin	2	0	60	6	0	60	1	60	12	5	0	12
Traverwood	2	0	90	6	0	90						
Nixon	2	0	54	6	0	48	1	54	12	5	48	18
Huron	2	12	48	6	0	48	1	0	12	5	48	12
Green	2	12	42	6	0	42	1	0	12	5	54	12

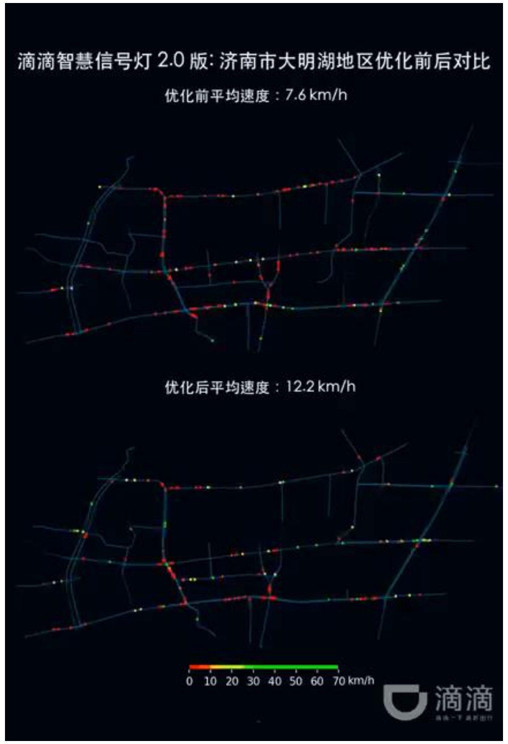
Generate new signal timing table for the Plymouth road corridor

Field implementation and deployment – Jinan, China

- Multiple intersections in Jinan China are deployed using data from Didi vehicles
- Semi-adaptive: adjust signal timing every week based on aggregated data due to low penetration
- Close-loop control: Detection->Evaluation->Optimization->Detection

Before and after study

City	Plan	Average Delay	Average Speed	
Daming Lake District (7 corridors, 43 intersections)	Weekend	-23.08%	+30.92%	Less congested
	Weekday morning peak	-7.70%	+5.91%	More congested
	Weekday evening peak	-9.56%	+8.73%	
	Weekday off-peak	-18.78%	+17.14%	Less congested

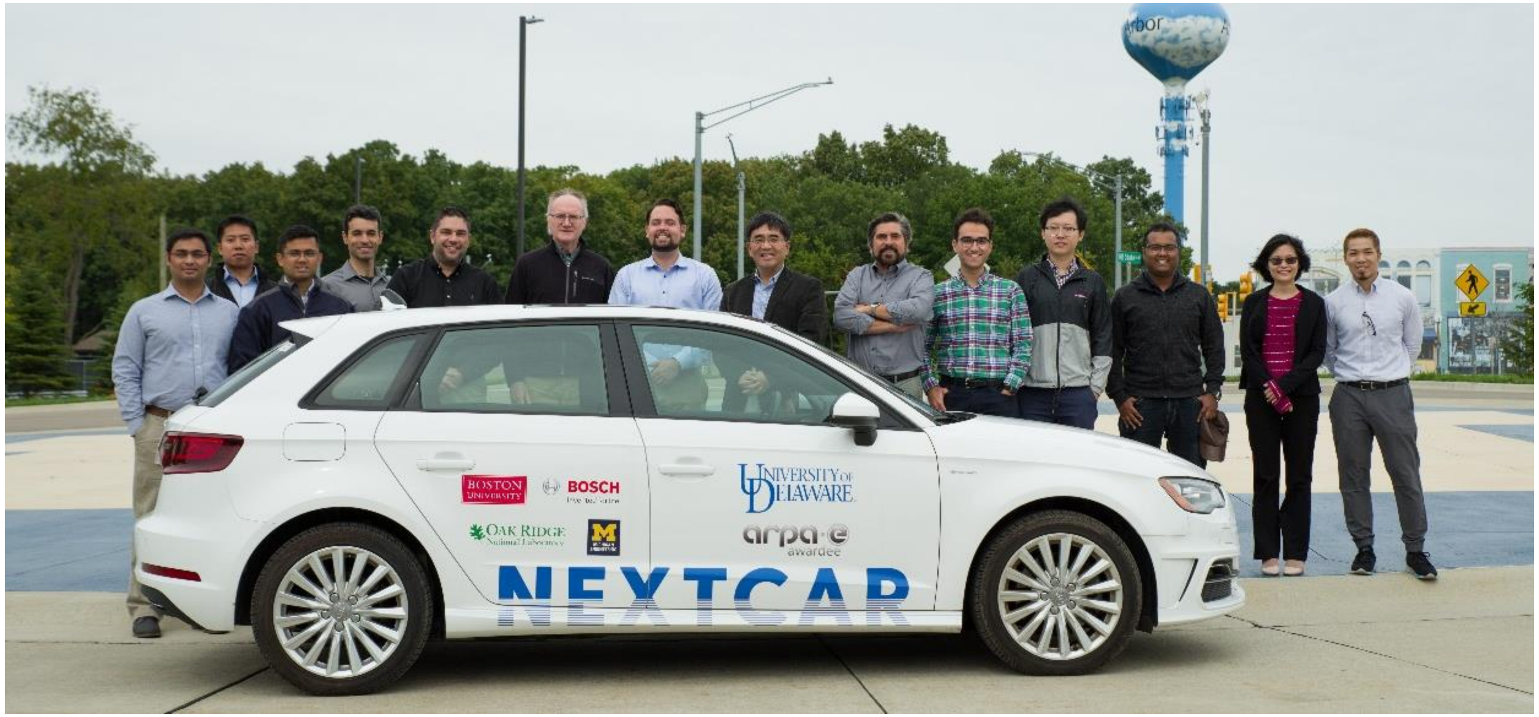


Why China? Opportunity for faster deployment

Simultaneous Optimization of Vehicle and Powertrain Operation Using Connectivity and Automation

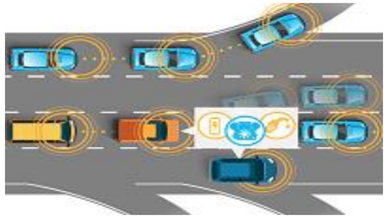
University of Delaware (Lead Organization)

Bosch, Boston University, University of Michigan, and Oak Ridge National Laboratory



Principal Investigator:

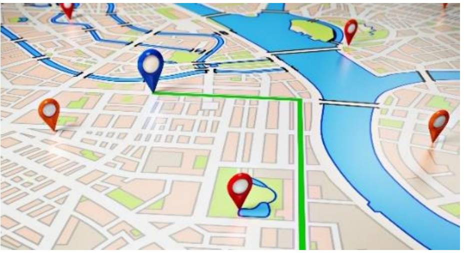
Andreas A. Malikopoulos



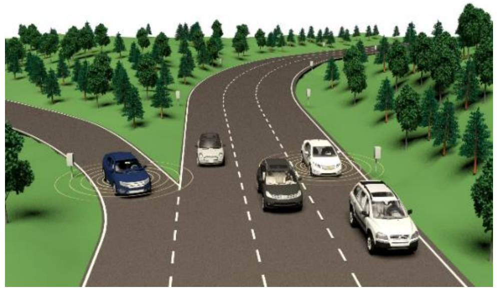
Major Work/Outcome

- Beneficial combination of CAV functions and powertrain control functions
- Cost effective CAV testing through Augmented reality
- SUMO model for Ann Arbor to study macroscopic effects of CAV functions

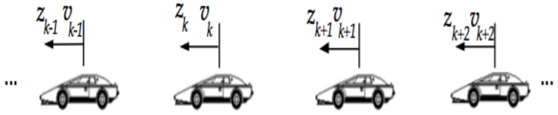
Beneficial Combination of CAV and Powertrain Controls



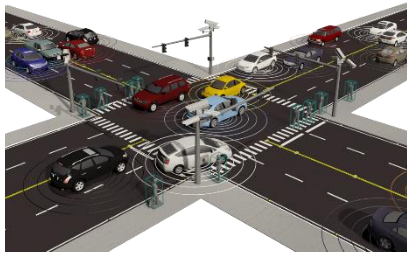
Eco-routing



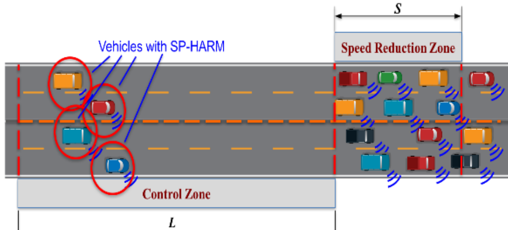
Vehicle Merging



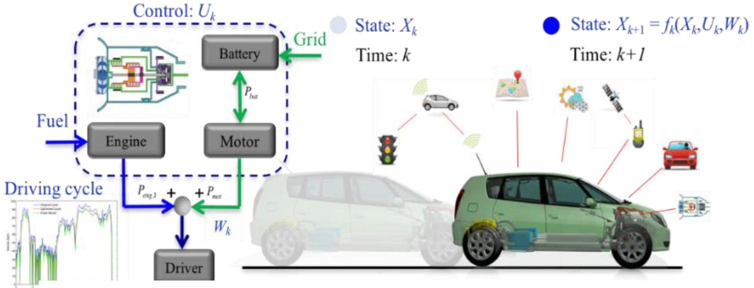
CACC



Eco-AND



SPD-HARM approach



Online optimization of the powertrain

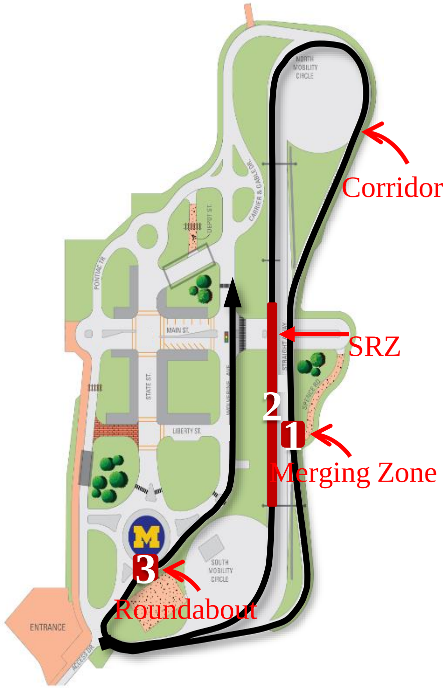
M1. B Table of Efficiency Improvements
Updated September 2018

Projection of the reduction attributable to supervisory, VD and PT controllers

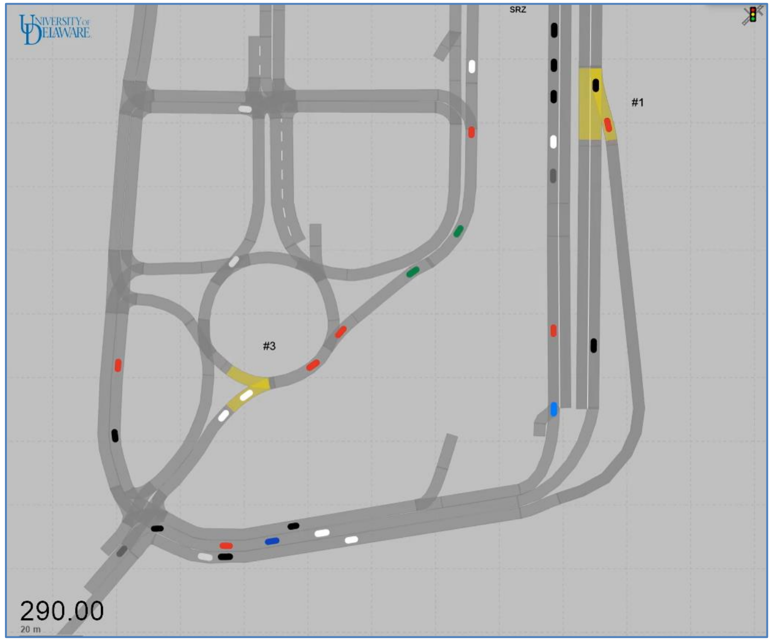
Application	Contributions on the X% Energy Consumption Improvement			
	Confidence	< 15%	15% to 25%	25% to 35%
Eco-routing (Supervisory controller)	H	o		
Vehicle coordination (VD controller)	M			o
CACC (VD controller)	M		o	
SPD-HARM (VD controller)	M	o		
Eco-AND (VD controller)	L		o	
Powertrain (PT controller)	M		o	

Levels of Confidence: L=Low, M=Moderate, H=High

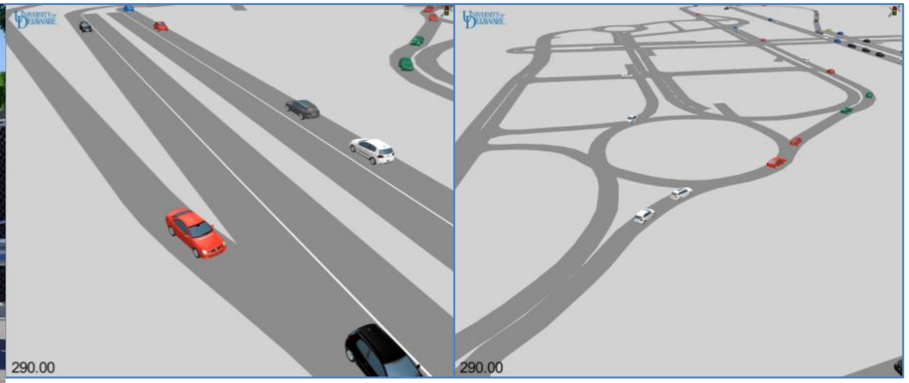
Augmented reality for cost effective CAV testing at Mcity

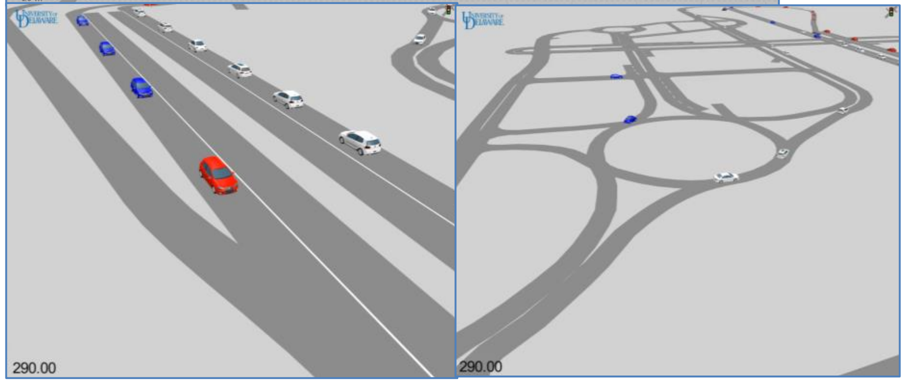


Baseline

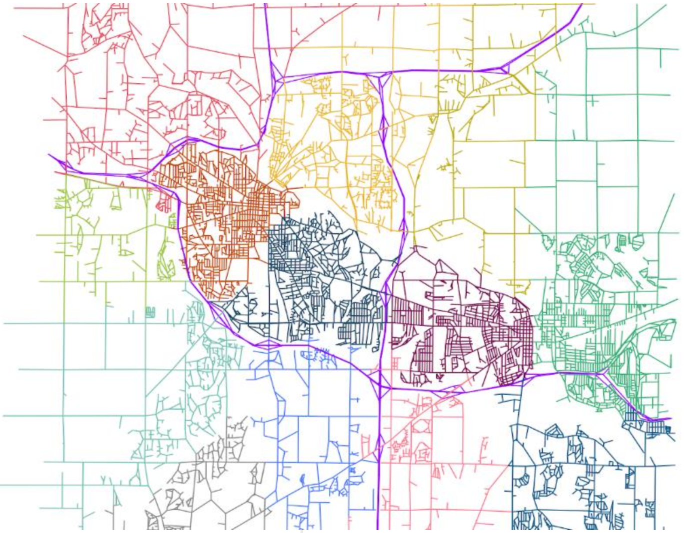


VD Controller

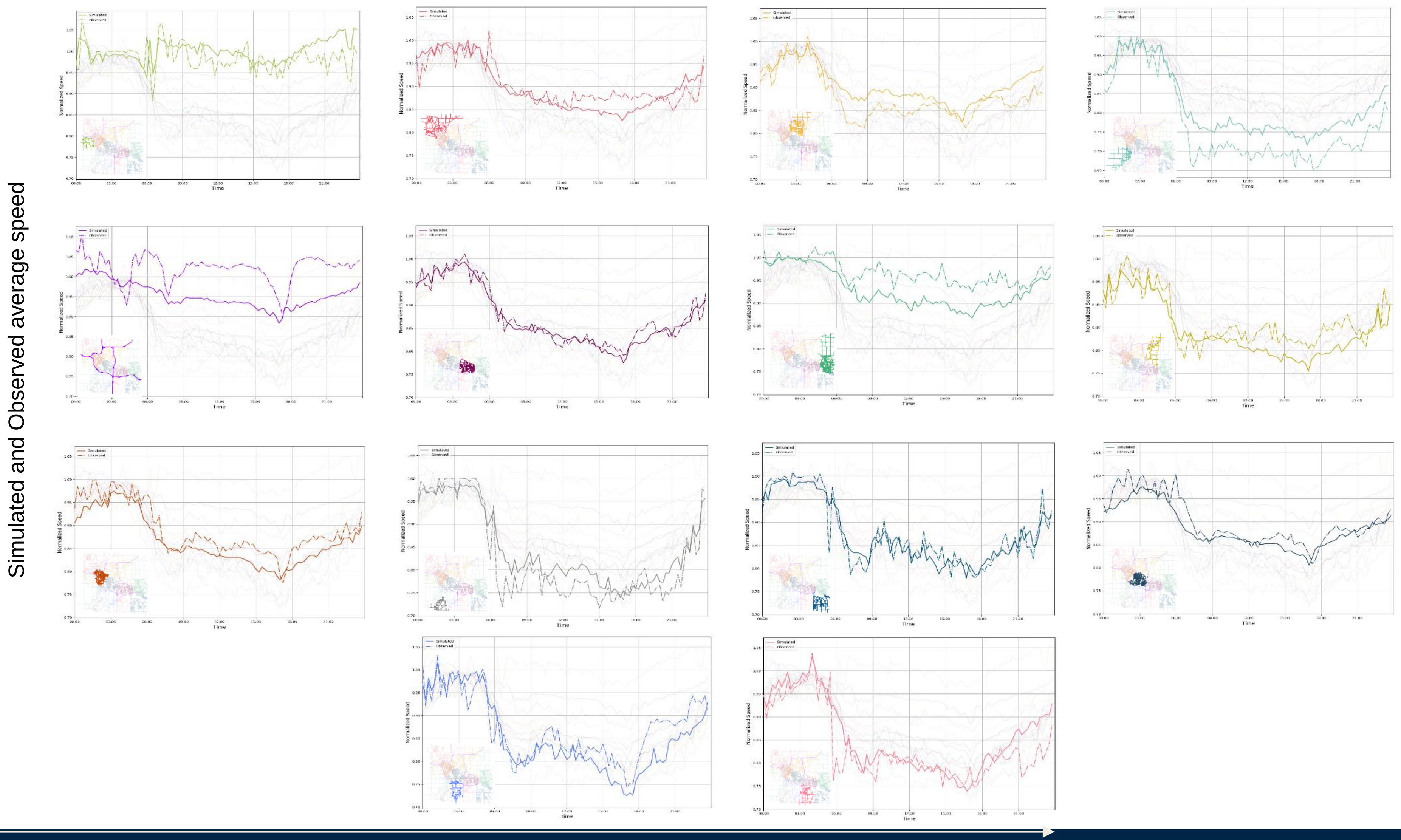




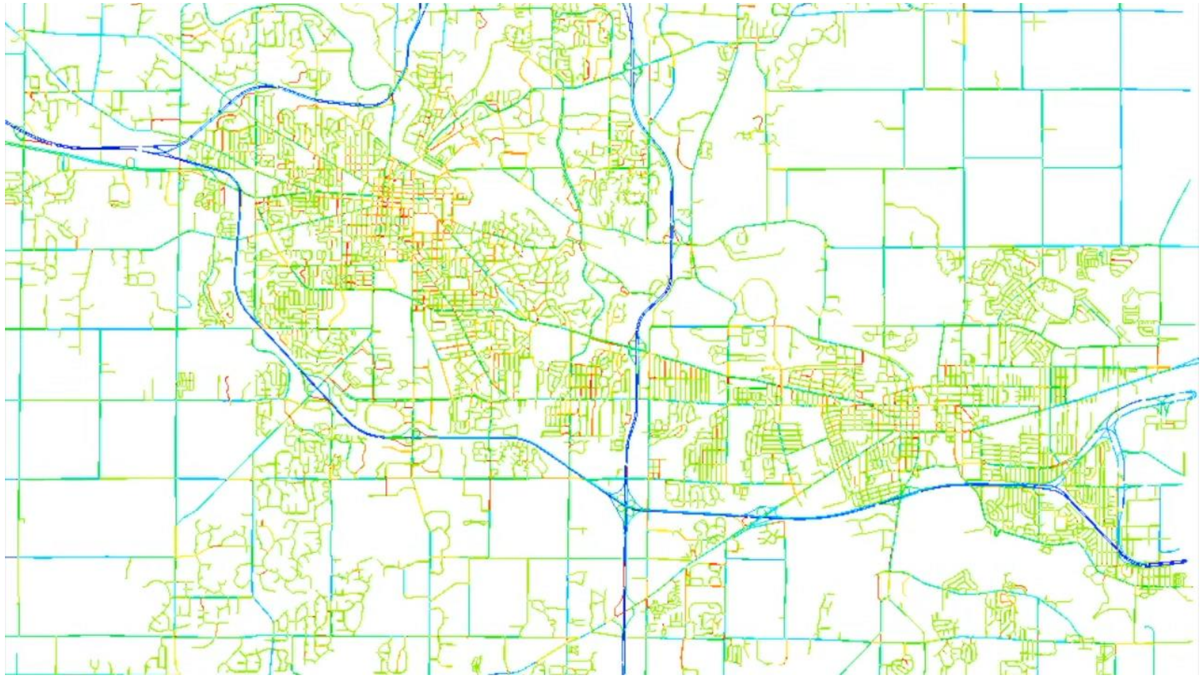
SUMO model for Ann Arbor (Calibrated by real data)

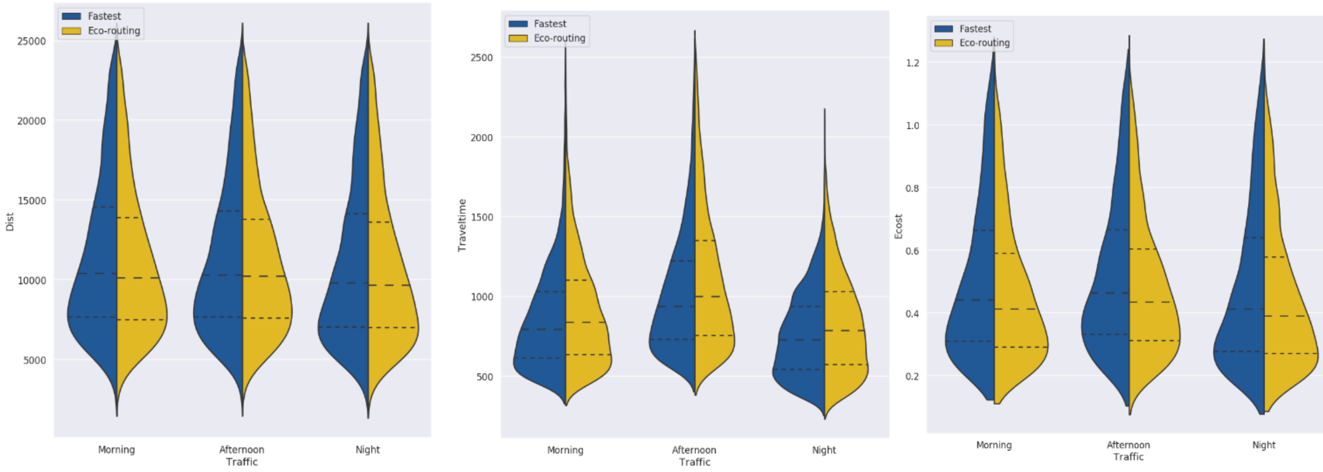


— Simulated and Observed average speed in each zone from 00:00 to 23:59



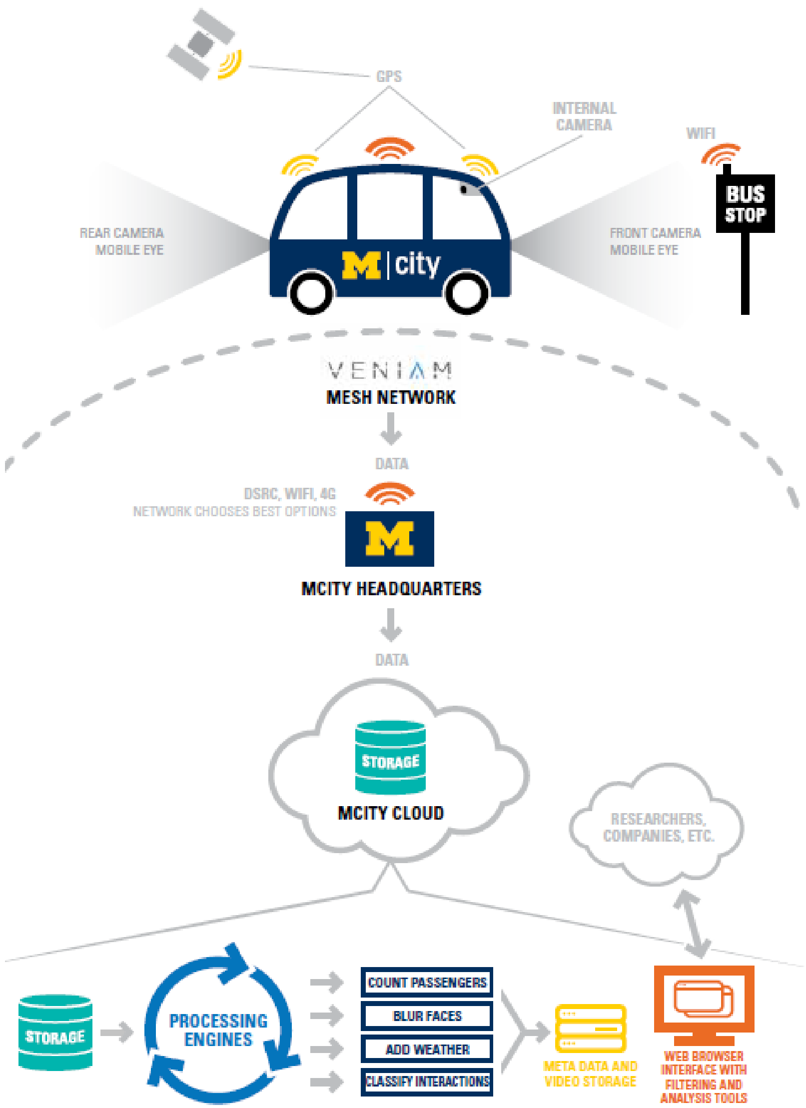
SUMO model for Ann Arbor (Eco-Routing results)





Method	Distance [m]			Travel Time [s]			Energy cost [$]		
	Mor.	Aft.	Night	Mor.	Aft.	Night	Mor.	Aft.	Night
Fastest	10234	10120	9437	793 Est.(731)	936 Est.(835)	726 Est.(680)	0.44	0.46	0.41
Eco-routing	9949	10055	9263	836 Est.(782)	999 Est.(880)	785 Est.(733)	0.41 Est.(0.36)	0.43 Est.(0.38)	0.39 Est.(0.34)
					Energy Saving [%]		6.5%	6.3%	5.3%

Mcity Driverless Shuttles (funding from Mcity members)



Mcity Driverless Shuttle Experience

- Video data shared with Mcity members
- User survey conducted by JDPower


Mcity Driverless Shuttle

A Case Study

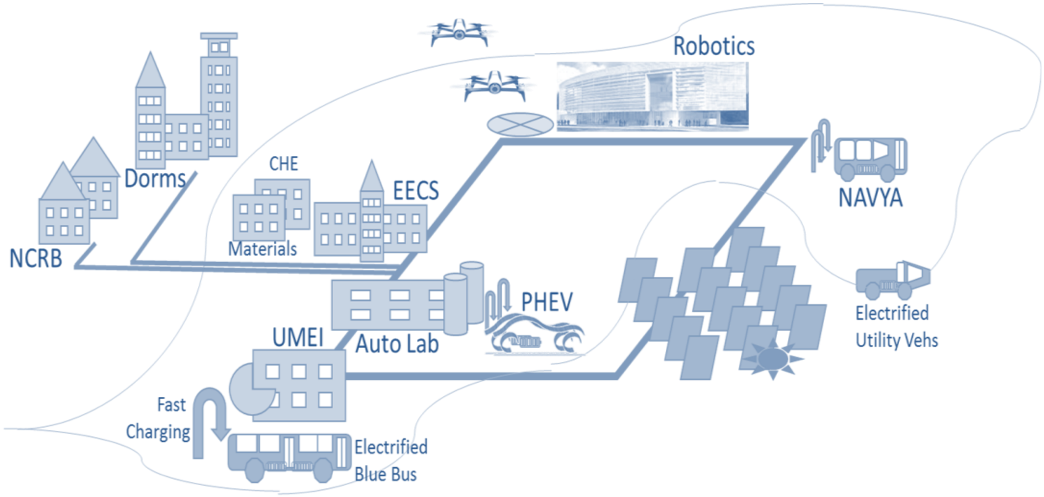
M | city
UNIVERSITY OF MICHIGAN

https://mcity.umich.edu/wp-content/uploads/2018/09/mcity-driverless-shuttle-case-study.pdf

Conclusion

- **Through DOE/DOT and Mcity members' investment, Mcity/Ann Arbor have become world's premier assets for CAV research**
- Mcity
  - Testing of CAV (HD-map, RTK, MKZ, V2X, 5G)
  - Augmented reality to simulate hundreds of other vehicles
  - In 6 software (Carsim, Prescan, Matlab/Simulink, Righthook, ANSYS, AVSimulation)
- Ann Arbor
  - Driving data (DOE CAV data, 8M miles + SPMD data 50M miles)
  - Plymouth + Washtenaw corridors smart signals instrumented
  - Calibrated model in Polaris and SUMO

How to leverage these unique assets to answer challenging CAV/Mobility research questions?



Ford
Leadership Circle Members
GM
HONDA
The Power of Dreams
M city
UNIVERSITY OF MICHIGAN
TOYOTA
APTIV
ECONOLITE Group, Inc.
StateFarm
DENSO
With Support From
MDOT
planet M
LG Life's Good
intel
verizon