2018 DOE Vehicle Technologies Office Review Presentation

Energy Impact of Connected and Automated Vehicles

PI: Huei Peng (UM)

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

June 18-21, 2018

Project ID #EEMS001

Overview

Timeline

- Start date: 2015/10/01
- End date: 2018/12/31
- Percent complete: 80%

Budget

- Total project funding
  - DOE share: $2,673,096
  - Contractor share: $297,101
- Funding received in FY17: $958,348
- Funding for FY18: $929,775

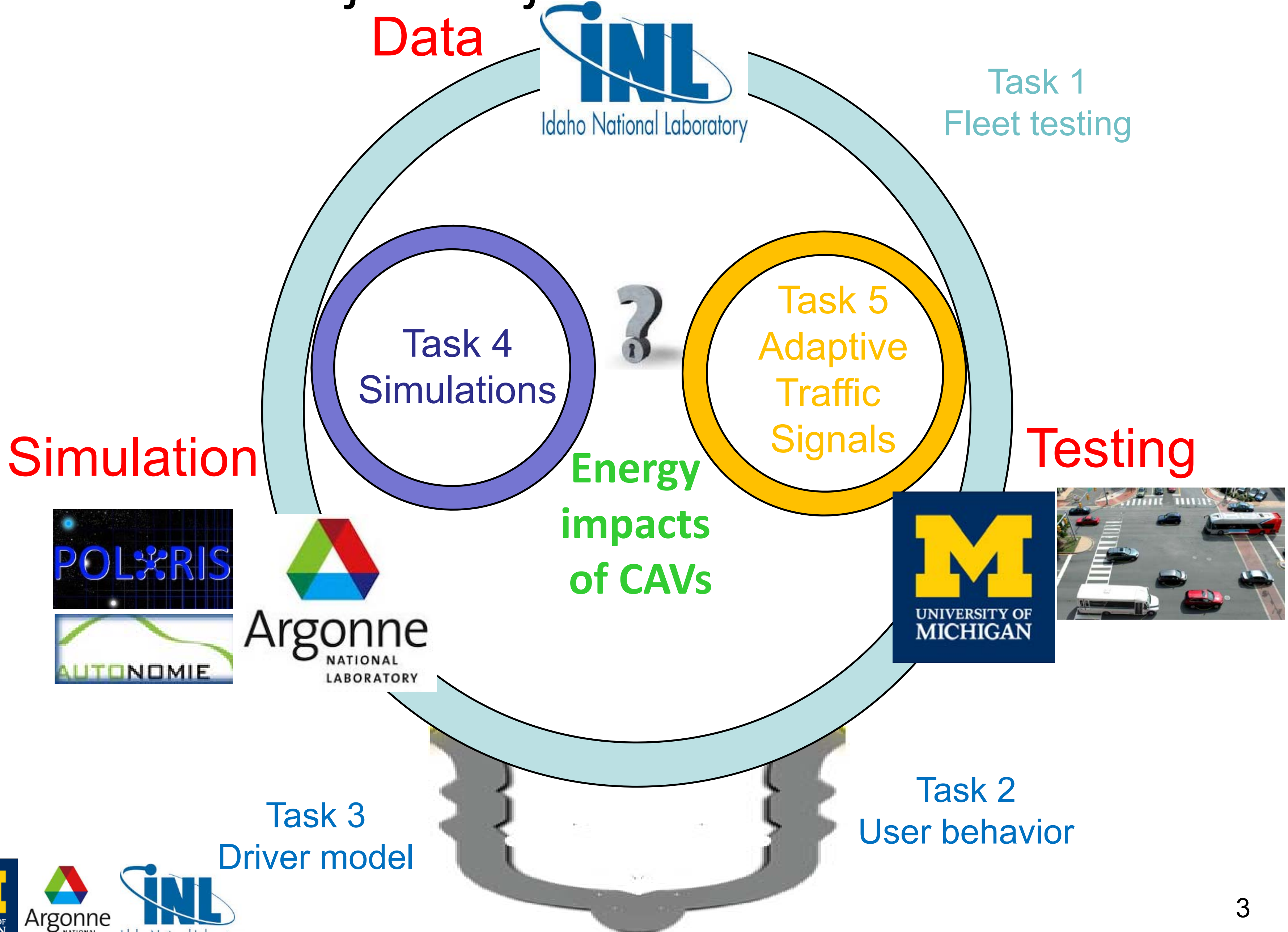
Barriers

- Lack of high fidelity models to predict the energy impact of CAVs--need real-world trip data and human behavior data for the development and calibration of these models
- Some CAV functions need cooperating infrastructure to function—which is lacking

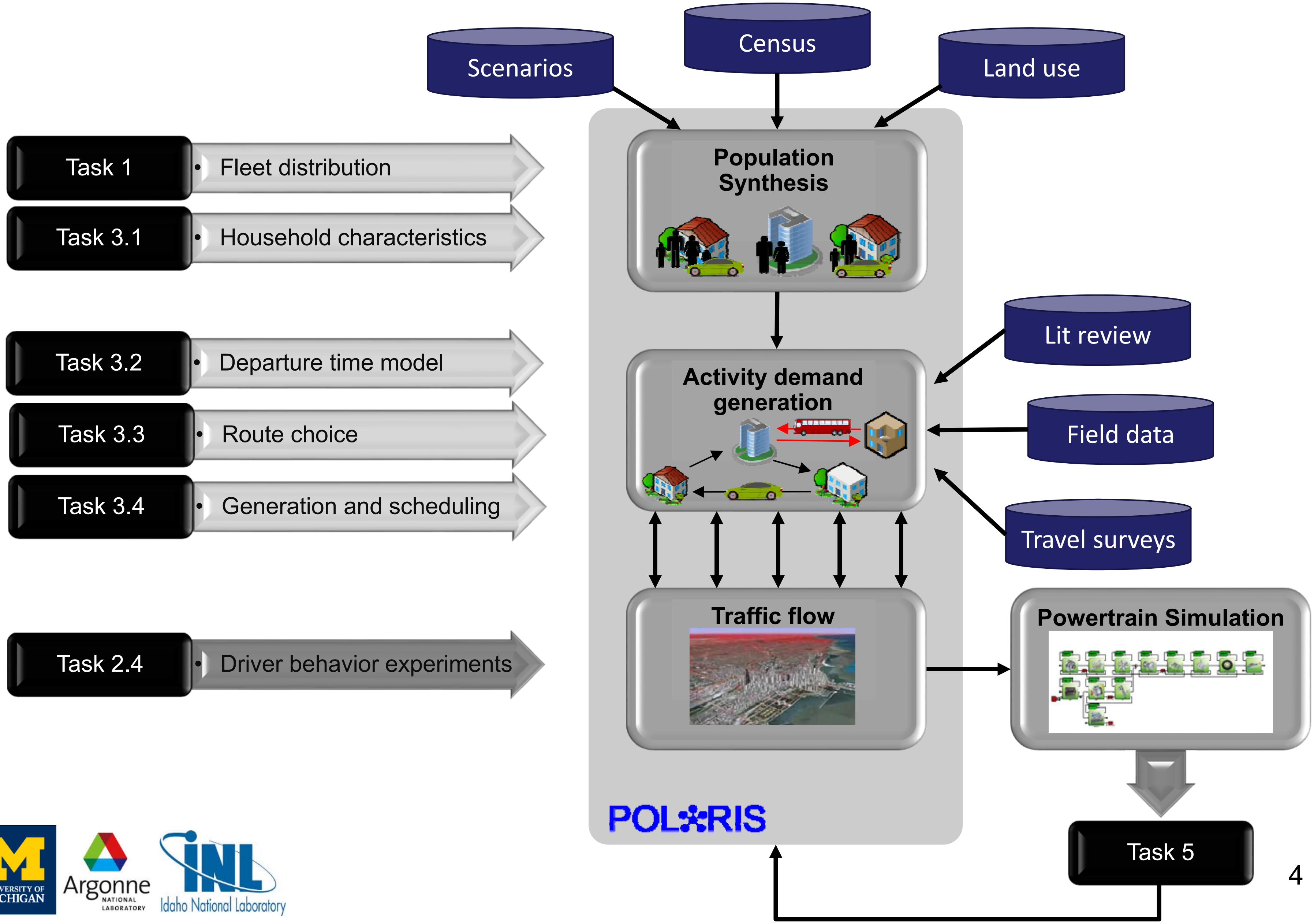
Partners

- University of Michigan (AA)
- Argonne National Lab
- Idaho National Lab

Project Objective-Relevance



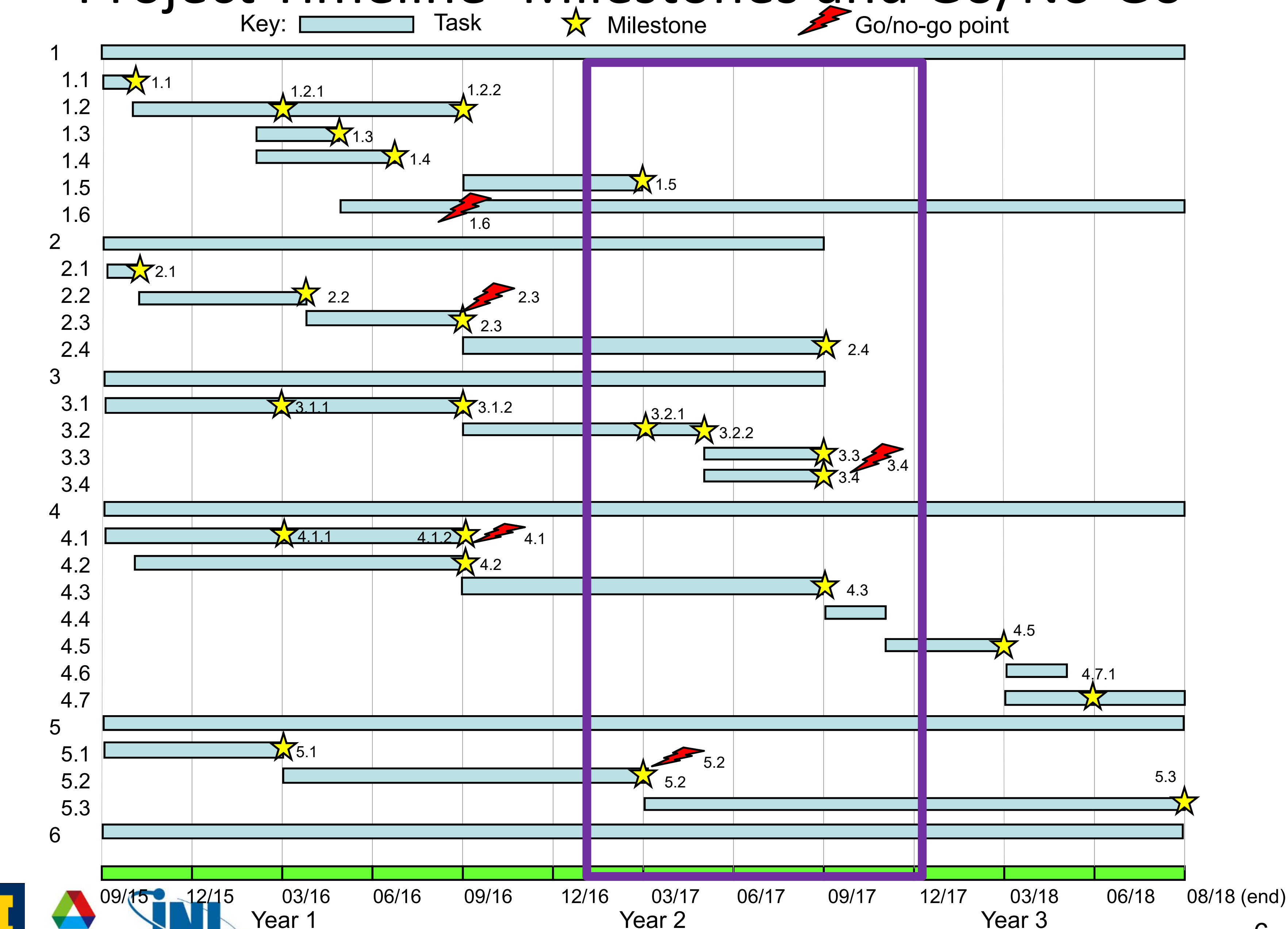
Interactions of Project Tasks (Task 4 centric)



Objectives / Relevance

- Deploy logging devices to assess energy usage on a large naturalistic fleet of passenger vehicles.
- Understand human behaviors/choices to develop better human decision models for simulations
  - Trip choices/patterns
  - User acceptance
- Test data used to develop model that can simulate the impact of energy consumption at a large scale (city of Ann Arbor) <u>for connected and automated vehicles (CAVs)</u>. The model will include human behaviors and key CAV functions (adaptive traffic signals, eco-routing, eco-approaching and departure

Project Timeline- Milestones and Go/No-Go



Approach/Strategy

- Five coordinated tasks among three leading CAV research organizations
- Leverage the connected vehicle fleet already deployed at UofM, add “energy focus”.
- Leverage INL’s expertise in monitoring and analyzing advanced technology vehicle performance and driving conditions to determine how driver behavior and usage conditions affect energy consumption of the vehicles.
- Leverage ANL’s expertise in modeling (Polaris and Autonomie)
- Final outcome: tools and test platforms that can be used to evaluate the energy impact of CAVs

Task 1: Instrumentation and data acquisition of energy related information

- Capturing travel, location, speed, and fuel/energy use on passenger vehicles (drivers' own vehicles & fleets)
- Ann Arbor, Michigan: 2016 – present.
- 500 FleetCarma C2 devices each plug into OBD-II connector
- Mix of powertrains (gasoline, PHEVs, EVs)
- Data sent over the air to UMTRI servers & loaded into relational databases (overall process delay ~ 2 hours)
- Data supports Task 4 of this project (O/D for Polaris, Argonne machine learning's work, and eco-routing & -approach)
- Shared with ANL, INL, EPA, UM TechLab students

Vehicle Fleet Statistics

✓ Accelerated pace of recruitments in 2017

215 devices in the database (~04/20/17)

420 devices in the database (04/16/18)

> 500 vehicles recruited

More than 4,500,000 miles of data collected

✓ Efforts to recruit PHEV&EV

Powertrain type	Number of vehicles(04/20/17)
ICE & HV	211 (98.1%)
PHEV & EV	4 (3 PHEV, 1 EV) (1.9%)
Total	215

Powertrain type	Number of vehicles(04/16/18)
ICE & HV	392 (93.3%)
PHEV & EV	28 (25 PHEV, 3 EV) (6.7%)
Total	420

	Number of Vehicles	Model
EV	3	Nissan Leaf
PHEV	14	Chevy Volt
	3	Ford Fusion Energi
	6	Ford Cmax
	2	Toyota Prius Plugin

Data Contents

<table>
<tr><th colspan="3">Data Name</th><th>Populated %</th><th>Sampling Period</th></tr>
<tr><td>GPS</td><td colspan="2">Latitude/Longitude (deg)</td><td>97.04 %</td><td>3 (sec)</td></tr>
<tr><td colspan="3">Vehicle Speed (km/h)</td><td>89.69 %</td><td>1 (sec)</td></tr>
<tr><td rowspan="8">Fuel Info</td><td colspan="2">Engine RPM (rev/min)</td><td>89.23 %</td><td rowspan="2">2 (sec)</td></tr>
<tr><td colspan="2">Mass Air Flow (g/s)</td><td>69.54 %</td></tr>
<tr><td colspan="2">Fuel Rate (L/hr)</td><td>2.58 %</td><td rowspan="4">5 (sec)</td></tr>
<tr><td colspan="2">Absolute Load (%)</td><td>72.96 %</td></tr>
<tr><td colspan="2">Short Term Fuel Trim B1 (%)</td><td rowspan="2">B1 alone : 49.40 %
B2 alone : 0 %
B1 & B2 : 72.70 %</td></tr>
<tr><td colspan="2">Short Term Fuel Trim B2 (%)</td></tr>
<tr><td colspan="2">Long Term Fuel Trim B1 (%)</td><td rowspan="2">B1 alone : 49.41 %
B2 alone : 0 %
B1 & B2 : 72.70 %</td><td rowspan="2">30 (sec)</td></tr>
<tr><td colspan="2">Long Term Fuel Trim B2 (%)</td></tr>
<tr><td rowspan="9">PHEV & EV only</td><td colspan="2">Odometer (km)</td><td>34.09 %</td><td>30 (sec)</td></tr>
<tr><td colspan="2">Ambient Temp ©</td><td>95.32 %</td><td rowspan="5">60 (sec)</td></tr>
<tr><td rowspan="3">Auxiliary Power (HVAC)</td><td>AirCon Power (KW)</td><td rowspan="2">93.73 %</td></tr>
<tr><td>AirCon Power (Watt)</td></tr>
<tr><td>Heater Power (Watt)</td><td>13.78 %</td></tr>
<tr><td colspan="2">Battery SOC (%)</td><td>97.40 %</td></tr>
<tr><td colspan="2">Battery Voltage (V)</td><td>78.06 %</td><td>5 (sec)</td></tr>
<tr><td colspan="2">Battery Current (A)</td><td>78.06 %</td><td>1 (sec)</td></tr>
<tr><td colspan="2">Is Driving, Charging (bool)</td><td></td><td>-</td></tr>
</table>

Fuel Consumption Calculation Study, EPA Data

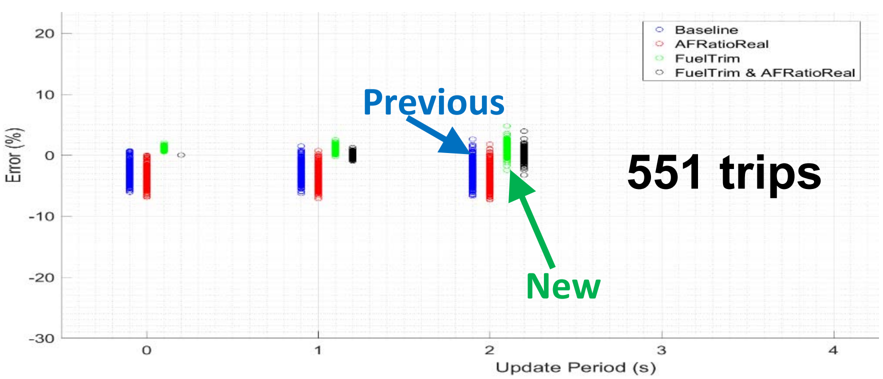
Compared 4 methods (MAF, MAF+AFR, MAF+LTFT, MAF+AFR+LTFT) with 4 rates (0.2, 0.5, 1.0, 10.0Hz)

Suggested to speed up to 1.0Hz to FleetCarma, compromised with 0.5Hz due to data size limit

Previous : 0.5Hz, MAF

New : 0.5Hz, MAF + LTFT

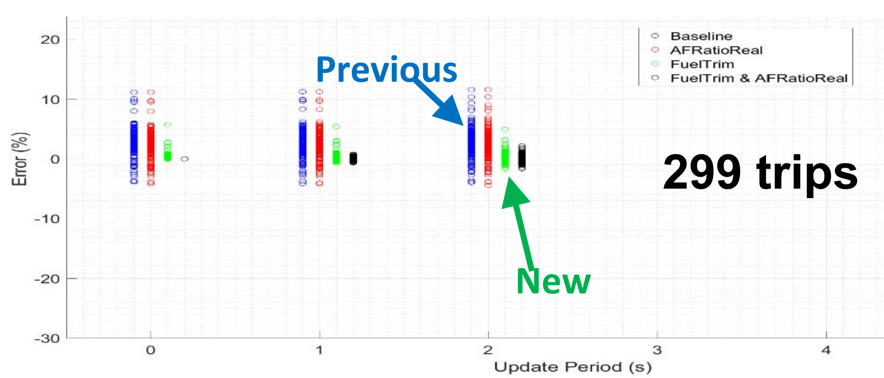
Error distribution, 2011 Subaru Outback



Standard deviation	MAF	MAF+ AFR	MAF+ LTFT	MAF+LTFT+ AFR
0.5Hz	2.02	2.05	1.40	1.35
1.0Hz	1.58	1.62	0.68	0.56

Previous → New

Error distribution, 2013 Chevy Cruze



Standard deviation	MAF	MAF+ AFR	MAF+ LTFT	MAF+LTFT+ AFR
0.5Hz	2.55	2.45	1.13	0.78
1.0Hz	2.37	2.26	0.87	0.26

Previous → New

Reference data : 10Hz, MAF + LTFT + AFR
(1.0mi<Travel Distance<10.0mi) : Daily commute range

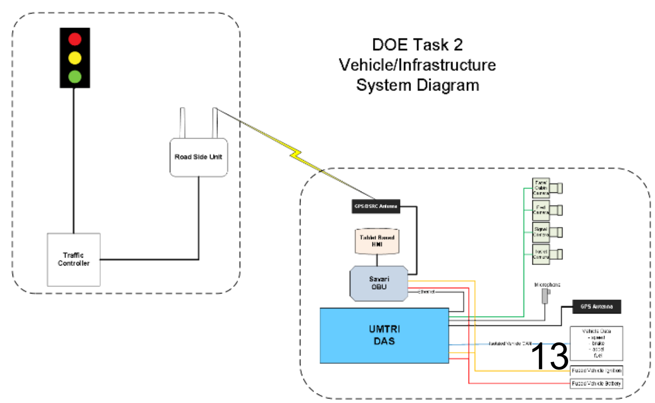
Technical Accomplishments Summary—Task 2

- The objective of task 2 is to develop CAV user functions and evaluate how users interact and accept the system:
  - Designed human participant experiment
  - Completed all experimental data collection
  - Developed data reduction and analysis methods
  - Finalizing data analysis and results interpretation

Task2: Experiment and Data Collection

– Experiment conducted at MCity
  - 32 participants
  - 7 scenarios in both control and treatment conditions:
    - Scenario 1: No speed changes to pass the green light phase- “Green Same Speed”
    - Scenario 2: Accelerate to pass green light “Green Speed Up”
    - Scenario 3: Decelerate to pass green light “Green Slowdown”
    - Scenario 4: Impossible to pass green light “Green Stop”
    - Scenario 5: No speed changes required to pass during NEXT green light “Red Through”
    - Scenario 6: Yellow dilemma zone-impossible to go through-“Yellow Stop”
    - Scenario 7: Yellow dilemma zone-possible to go through-“Yellow Through”

– Vehicle instrumentation
  - An existing UMTRI Honda test vehicle
  - Cameras (front view ,driver face and over the shoulder)
  - DAS, GPS and software update



Task2: Data Collection Course in Mcity

- Drivers followed the course outlined in blue arrows.
- Data collection centered around the run from the green cone to the red stop line
- Tablet began receiving SPAT information from the RSU around orange box (about 100 meters out)

Task 2: Preliminary Results on Subjective Data

- A post study questionnaire with **13 questions** was distributed to all participants to collect their opinions of the system
- The preliminary results were from a subset of 25 participants who completed the study earlier
- High acceptance rate (about 82%)
- Most users think the **signal remaining time** and **recommended speed** are most useful
- A Principle Component analysis was conducted to divide the 13 questionnaires in to 5 categories
  - User-friendliness
  - Reliability and usefulness
  - Distraction
  - Safety
  - Energy consumption

	Component				
	1st	2nd	3rd	4th	5th
q4	0.807				
q1	0.774				
q3	0.763				
q13	0.742				
q8		0.885			
q2		0.863			
q6		0.607			
q7		0.605			
q5			-0.888		
q9			0.802		
q11				0.934	
q10					0.835
q12					-0.771
Eigenvalue	5.617	1.819	1.336	1.118	1.086
Percentage	43.2	14	10.3	8.6	8.4
Cumulative	43.2	57.2	67.5	76.1	84.5

Q1: user-friendliness

Q2: reliability and usefulness

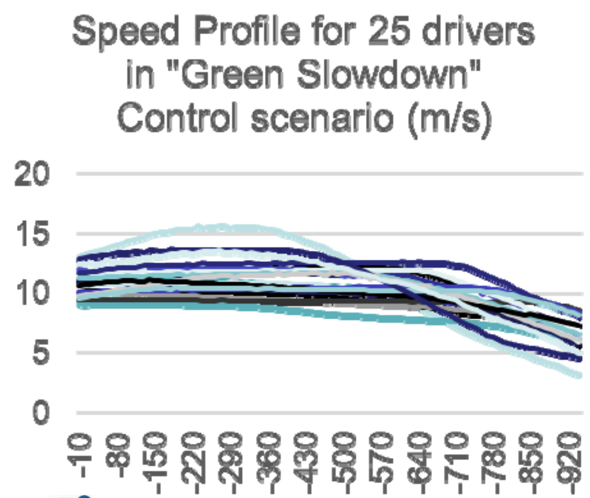
Q3: distraction (Low distraction)

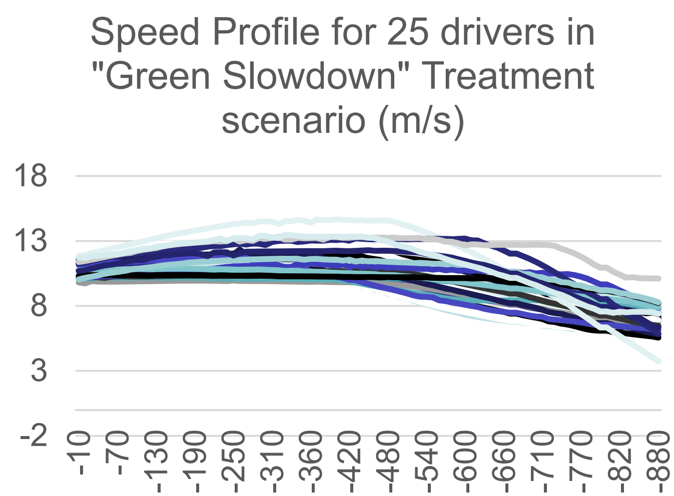
Q4: driving safety (driving risk)

Q5: energy saving (energy consumption)

Task2: On-going Analysis-Modeling and Predicting Drivers' Reaction

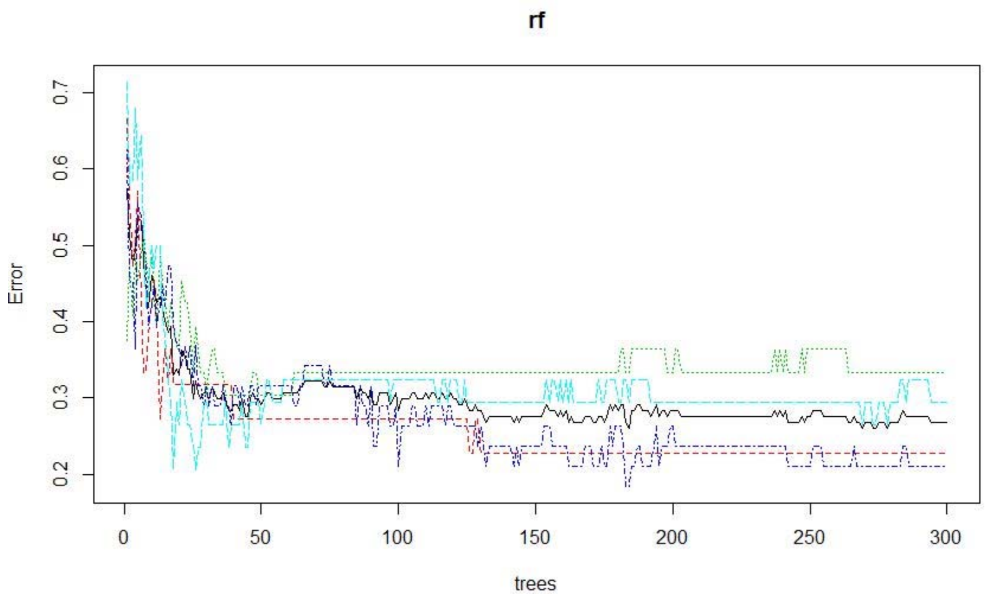
- The goal is to model whether and how drivers will change their behavior. Independent variables include:
  (1) Demographic information: age, gender, education, years of driving
  (2) Drivers' evaluation on this system: 13 questions from the questionnaire
  (3) Traffic information: Scenarios, Speed and acceleration when the tablet began to work
- Methods include Principle Component Analysis (PCA) for clustering and Random Forest for prediction

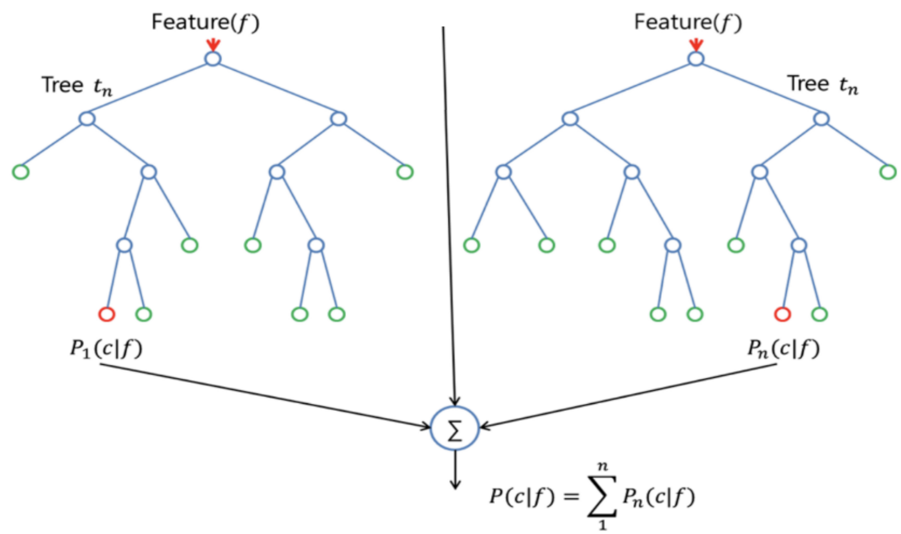




Task 2: Random Forest Analysis for Prediction

- Random Forest is a supervised learning algorithm, which operates by constructing a series of decision trees at training time and merges them together to get a more accurate and stable prediction as output.
- Used to <u>predict driver stopping behavior</u> at intersections in this study.
- Importance of each variable will also be assessed.





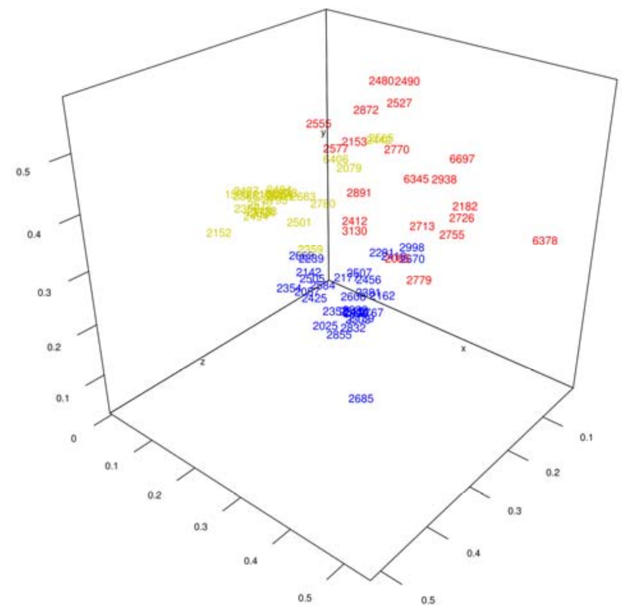
Source: https://towardsdatascience.com/the-random-forest-algorithm-d457d499ffcd

Task 3: Driver Behavior Modeling

- Overview
  - General Goal:
    - Model the impact of CAVs on people's travel behaviors and explore its implications for transportation energy consumption
  - Major Components:
    - Activity **pattern mining**: data-driven approach
      - Investigate the current household activity patterns in the City of Ann Arbor
    - Household activity **pattern optimization**: theoretical modeling
      - Study the potential impact of CAVs on willingness to share rides, route choice, departure time choice, and energy consumption

Task 3: Driver Behavior Modeling | Pattern mining

- Goal:
  - Extract activity patterns from trajectory data and land-use data, and then characterize the drivers using the activity patterns
- Data sources:
  - Trajectory data from Safety Pilot (SP) project and land-use data
  - Survey data from 396 participants of SP
    - Demographic characteristics: gender, age, level of education, etc.
    - Household information: number of cars, number of children in the household, etc.
- Method:
  - Principal component analysis
  - Hierarchical clustering



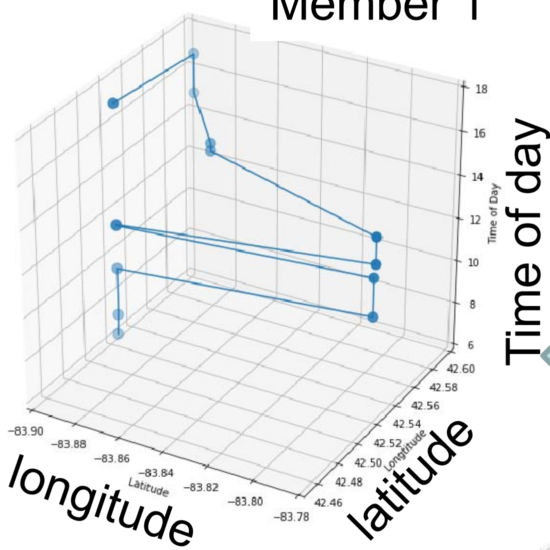
Task 3: Driver Behavior Modeling | Pattern optimization

- Goal
  - Study the impact of CAVs on people's travel costs and willingness to share rides at the household level
- Question
  - Since autonomous vehicles can reposition themselves, some situations previously requiring two regular vehicles may only require one autonomous vehicle.
  - Should those households currently having two vehicles replace their **two** regular vehicles by **one** autonomous vehicle in the future? Will there be a lot of schedule conflicts?
- Assumption of people's travel behaviors
  - Given a list of activities to attend, household members choose their travel mode and departure time to minimize their total travel cost

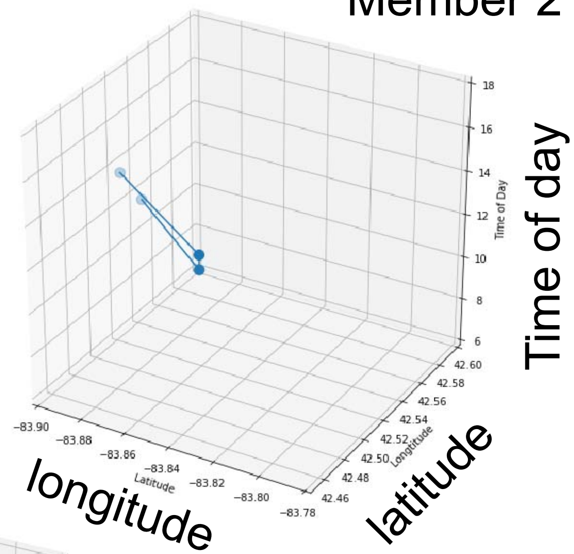
Task 3: Driver Behavior Modeling | Pattern optimization

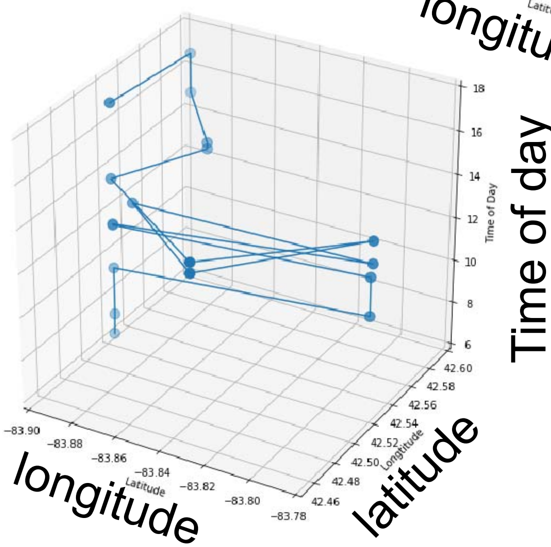
- Typical Scenario: Shared trips (schedule relaxation < 30 mins)

Member 1



Member 2





In this example, schedules are relaxed by 12 minutes, but VMT increases by 15%.

Task 3: Driver Behavior Modeling | Pattern optimization

- Main findings (1 AV serving two family members):
    - Time: the household members sometimes have to relax their work schedules by more than 30 mins
    - Energy: vehicle miles traveled can decrease due to shared trips, but sometime increase due to detours
- Implication:

– for family with many activities, travel far away, and have very different activity locations and schedules, one shared AV cannot provide the mobility needs.

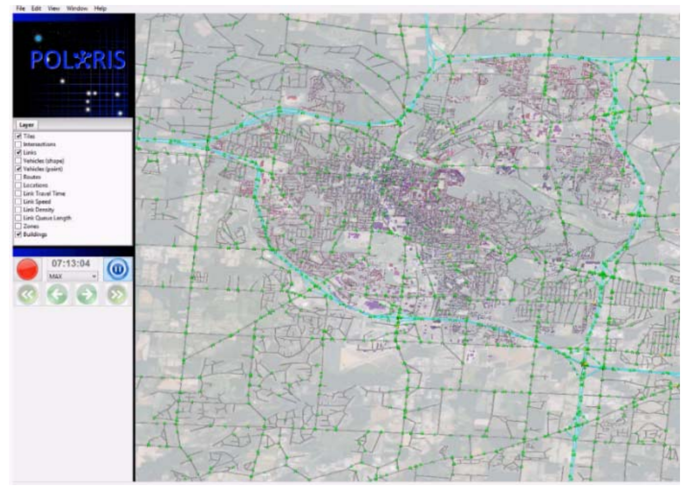
– **Next: Multiple shared AVs serving multiple families**

UNIVERSITY OF MICHIGAN Argonne NATIONAL LABORATORY Idaho National Laboratory

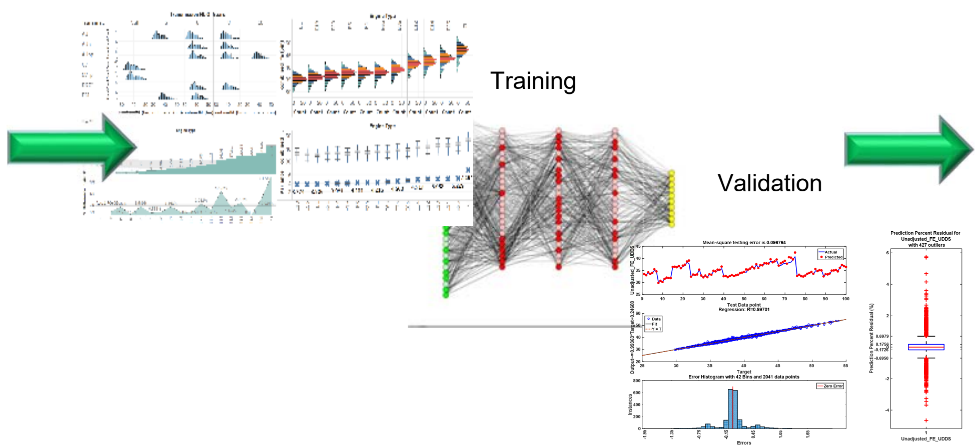
Technical Accomplishments—Task 4

- Developed POLARIS regional travel demand/energy use simulation model for Ann Arbor
- Developed algorithms/software to convert GPS traces into individual travel and network performance data
- Developed machine learning framework to estimate the vehicle energy consumption of a wide range of vehicles under real world driving

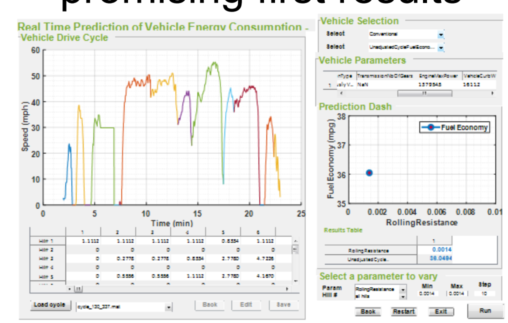
Polaris model of Ann Arbor



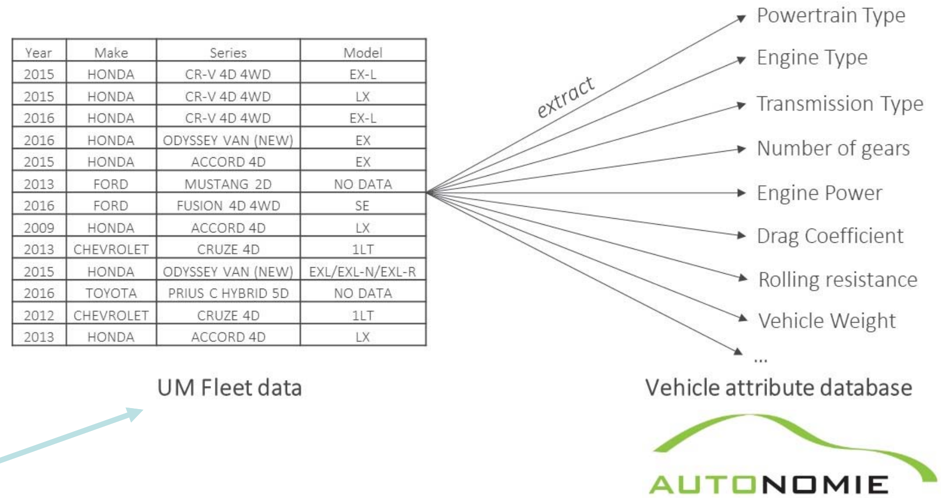
UofM On-Road data (Task 1) complemented with Autonomie simulation results (from POLARIS & RWDC)



Work in Progress, promising first results



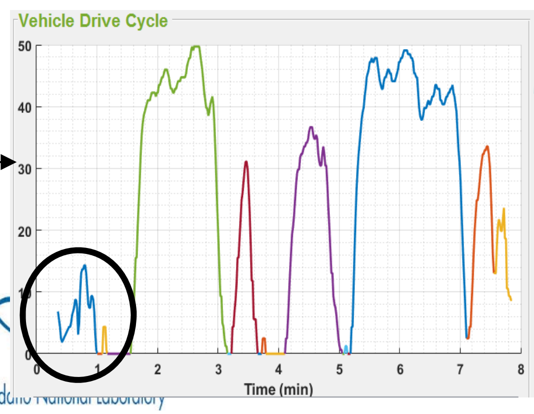
Machine Learning Approach and Progress



Year	Make	Series	Model
2015	HONDA	CR-V 4D 4WD	EX-L
2015	HONDA	CR-V 4D 4WD	LX
2016	HONDA	CR-V 4D 4WD	EX-L
2016	HONDA	ODYSSEY VAN (NEW)	EX
2015	HONDA	ACCORD 4D	EX
2013	FORD	MUSTANG 2D	NO DATA
2016	FORD	FUSION 4D 4WD	SE
2009	HONDA	ACCORD 4D	LX
2013	CHEVROLET	CRUZE 4D	1LT
2015	HONDA	ODYSSEY VAN (NEW)	EXL/EXL-N/EXL-R
2016	TOYOTA	PRIUS C HYBRID 5D	NO DATA
2012	CHEVROLET	CRUZE 4D	1LT
2013	HONDA	ACCORD 4D	LX

Data Analysis

- Vehicle Model with Fleet
- Map Matching with Fleet
- Feature Selection
  - Model with Cycle Features
  - Model with Trip



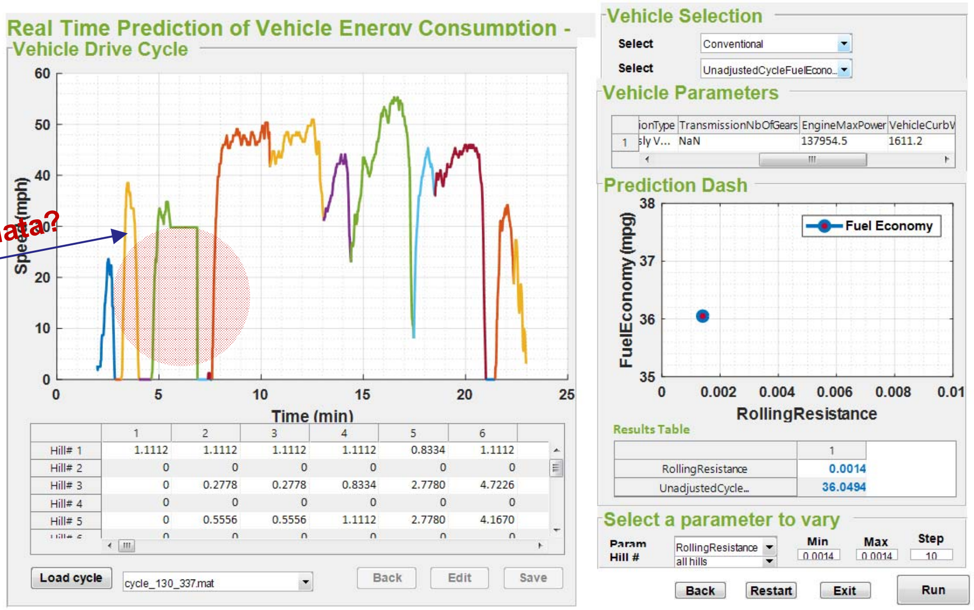
Each cycle is composed of several links in which natural cubic splines are fitted with the coefficients basis estimated.

Results - Most Fuel Economy Prediction within 5%

Vehicle ID	Cycle ID	RW*	ML*	Error
129	284	27.74	29.8	7.4%
129	285	31.25	29.66	-5.1%
129	288	23.32	24.09	3.3%
129	290	25.01	25.1	0.4%
129	297	27.38	26.7	-2.5%
130	337	41.01	36.04	-12.1%
130	338	35.75	36.27	1.5%
130	340	30.65	32.02	4.5%
130	341	30.46	30.53	0.2%
188	139	31.85	33.58	5.4%
188	141	41.19	38.65	-6.2%
...				

**mpg*

Erroneous data?



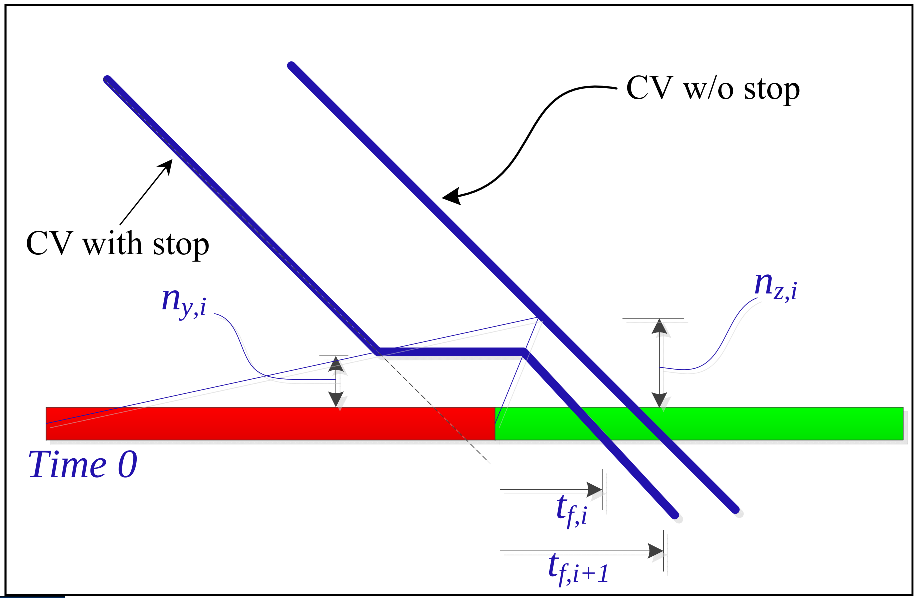
- Future work:
  - Continue map matching work (match collected vehicle data with POLARIS maps for route segmentation)
  - Integrate ML vehicle energy model into POLARIS for mode and route selection
  - Develop traveler mode selection including energy
  - Perform POLARIS simulations using ML energy model

Technical Accomplishments—Task 5

- Objectives
  - Design adaptive signal control algorithms
  - Implement and evaluate the models in both simulation environment and real world testbed
- Technical Approach
  - Modeling: We developed volume estimation and adaptive control algorithms using connected vehicle trajectory data
  - Implementation: We implemented the proposed algorithms in Jinan, China
- Uniqueness
  - Traffic state estimation and control using low penetration of CV data
  - First large-scale implementation of detector free CV based adaptive signal control

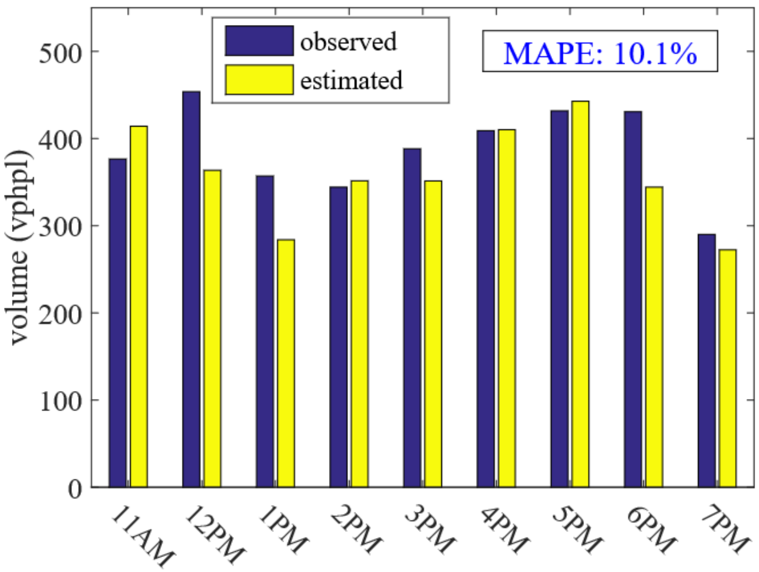
Technical Accomplishments—Task 5

- Traffic State Estimation
  - Consider CV as two main types:
    - CV with stop → vehicles queuing ahead of the CV
    - CV without stop → vehicle queue did not affect the CV
  - Assume vehicle arrivals follow a time dependent Poisson process
  - Maximum likelihood estimation with expectation maximization to estimate the arrival rate



Two example vehicle trajectories

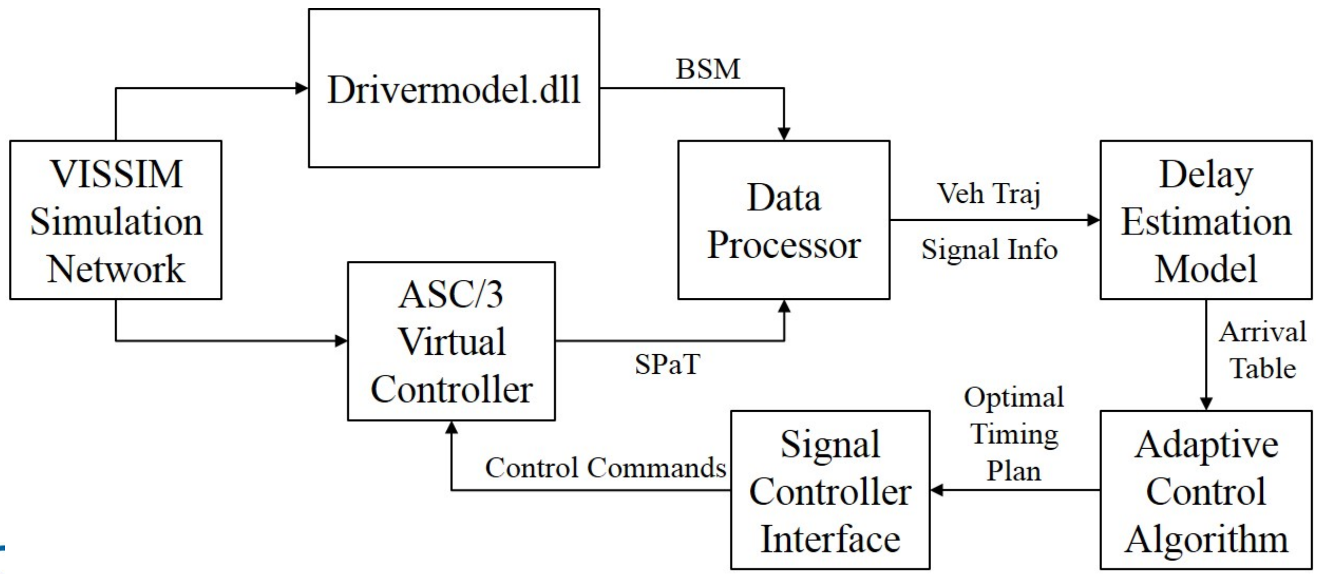
Penetration Rate : ~3%



Traffic volume can be estimated accurately

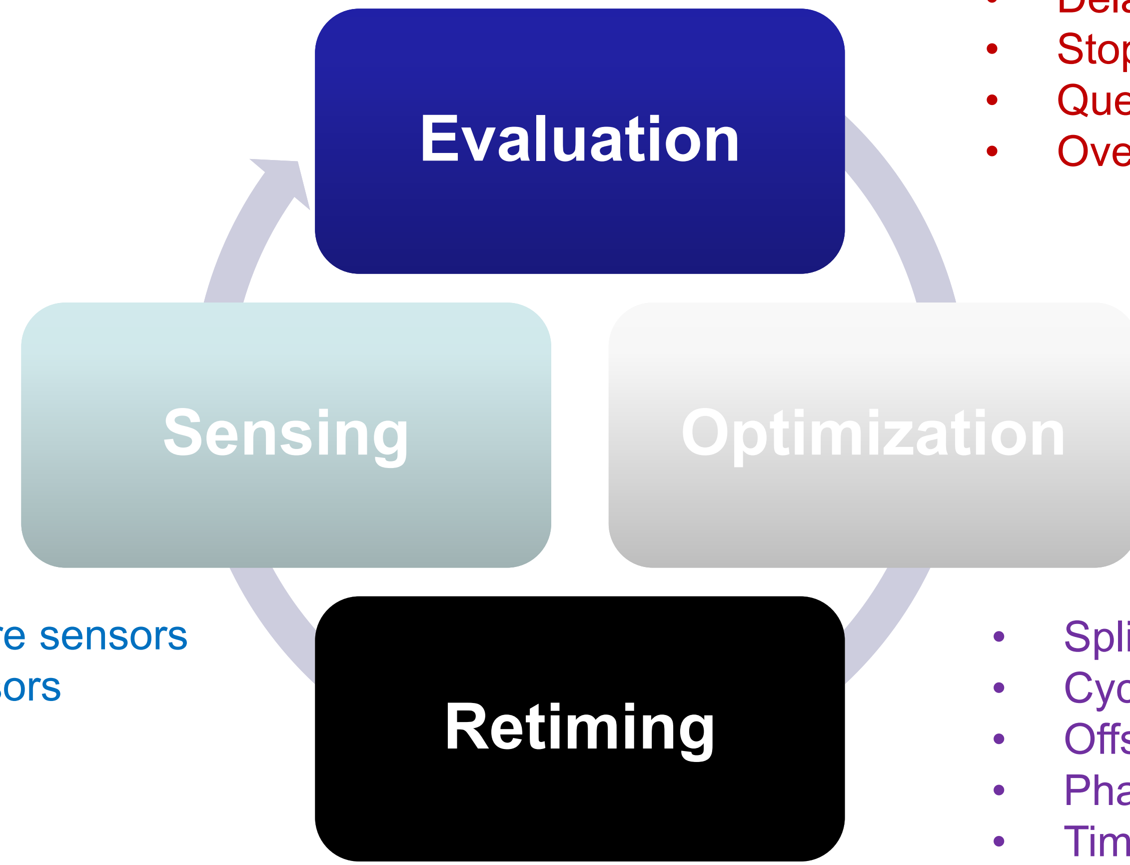
Technical Accomplishments—Task 5

- Adaptive Signal Control Algorithm
  - Dynamic programming (DP) based optimization
  - A baseline timing plan is generated based on historical data
  - If no CV is observed during, the baseline timing is executed
  - If CV trajectories are observed, the timing plan is updated dynamically based on the estimated delay
- Testing in software-in-the-loop simulation environment:



Technical Accomplishments—Task 5

- Field Implementation Process



- Delay
- Stops
- Queue length
- Oversaturation

- Splits
- Cycle length
- Offset
- Phase sequence
- Time-of-day plan

- Infrastructure sensors
- Mobile sensors

Technical Accomplishments—Task 5

- 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%
	Weekday morning peak	-7.70%	+5.91%
	Weekday evening peak	-9.56%	+8.73%
	Weekday off-peak	-18.78%	+17.14%

Responses to Previous Year Reviewers' Comments

- *Q1, Reviewer 1: The reviewer said that the approach being pursued should yield valuable data and impactful results that the reviewer looked forward to hearing about.*
- We did not have much data last year because the dongles installation just started. We are happy to report significant amount of data produced (**4.5 million miles**).

Responses to Previous Year Reviewers' Comments

- *Q4, Reviewer 6, The reviewer stated that it is not clear how the tasks are related to each other and whether/how delays or issues in one will affect the others.*
- We added a slide (4) to clearly show how all the data/model developed lead to impact Task 4, which developed a CAV model for the city of Ann Arbor.

Challenges and Barriers

- Data recording rate, fleet diversity, and CAN data decoding to generate useful data for the Polaris/Autonomie models
- Recruiting of volunteer drivers, especially regarding their “confidence of the OBD dongles”
- Interpreting the human behavior test results and incorporate into the POLARIS model
- Implementing adaptive traffic control requires coordination from the City

Future Work

- Task 1: Data collection will continue, data will continue to be shared with ANL, INL. EPA and UM researchers.
- Task 2: Complete driver behavior modeling analysis.
- Task 3: Analyze the impact of AVs on mobility at the household level using an activity based model.
- Task 4: Implement the new energy ML model in POLARIS; develop new algorithm for traveler decisions that include energy.
- Task 5: Implementation of adaptive traffic signal algorithms in Ann Arbor.

Summary

- Task 1: Collected FleetCarma data from > 500 vehicles, 550k trips, 4.5M miles, shared within the team, EPA, Tech Lab students.
- Task 2: Completed all experimental data collection from 32 participants, reduced driving data by using geo-fences and conducted analysis on user acceptance and behavior measures.
- Task 3: Modeled baseline activity patterns of Ann Arbor, conducted analysis of the impact of CAVs on traffic and energy consumption.
- Task 4: Embedded Energy Estimation function in POLARIS based on machine learning.
- Task 5: Traffic state estimation under low CV penetration rate; developed adaptive signal control algorithm--Data collection from 6 intersections on Plymouth Rd, Ann Arbor.
- Two highlighted case studies using Ann Arbor data and model.

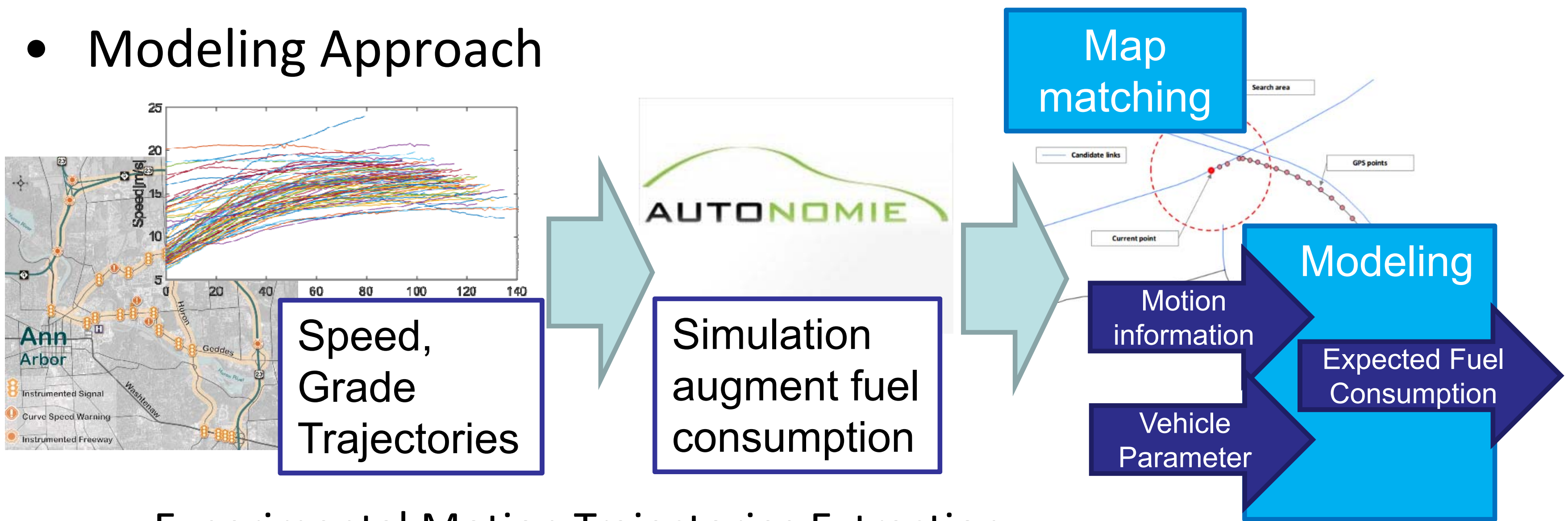
Technical Back-Up Slides

Technical Backup:

Case Study 1: Eco-Routing Using Real Ann Arbor Data

Fuel Consumption Model Overview

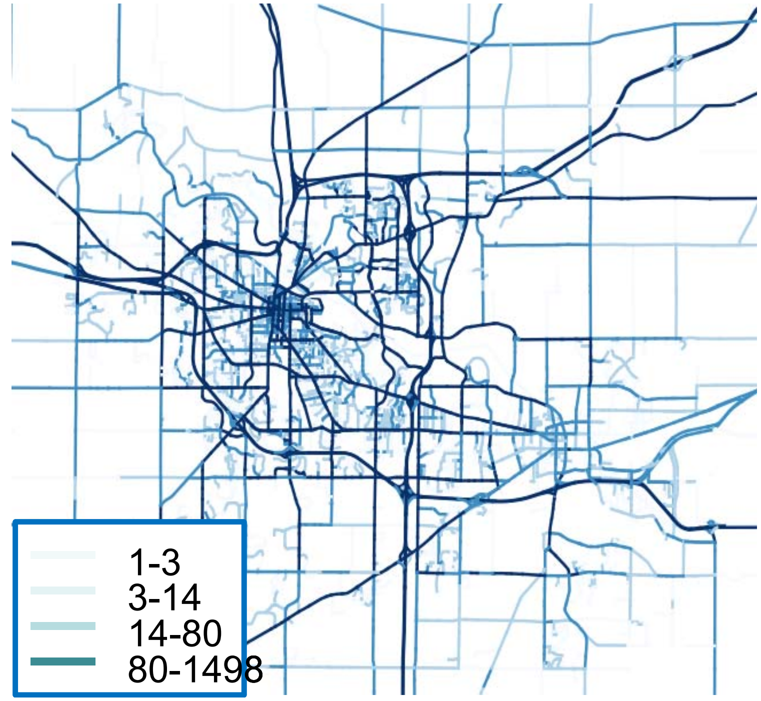
- Requirements
  - Fast Enough: Can evaluate routable network cost
  - Complex Enough: Can model all kinds of links
- Modeling Approach



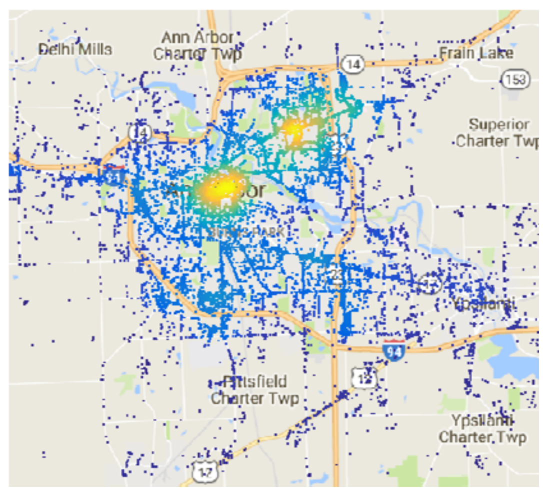
  - Experimental Motion Trajectories Extraction
  - Fuel Consumption Simulation Augmentation
  - Map Matching and Link Data Driven Model Training

Data Description

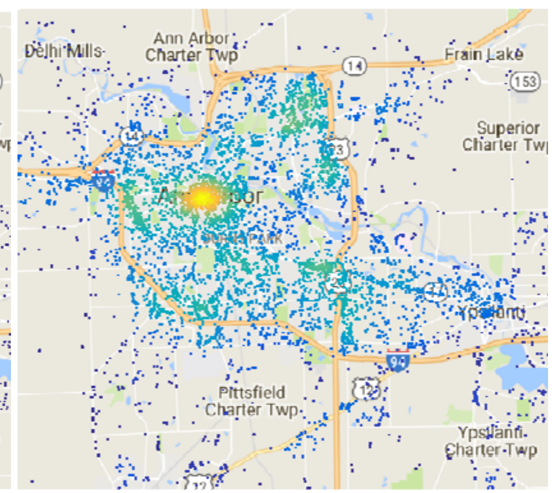
- Sample Size 321,945 trips
  - Covered 9,745/11,506 links in the Ann Arbor area (both local streets and surrounding highways)
  - 5,599 links with more than 100 trips
  - Query Criteria
    - Trip length 10 min – 1 hour
    - Trip Distance > 300 m
  - Total Distance: 2,281K miles
  - Total Time: 93,926 hours



3031 frequently visited OD pairs identified
80 starting locations, 123 ending locations



Trip Origins



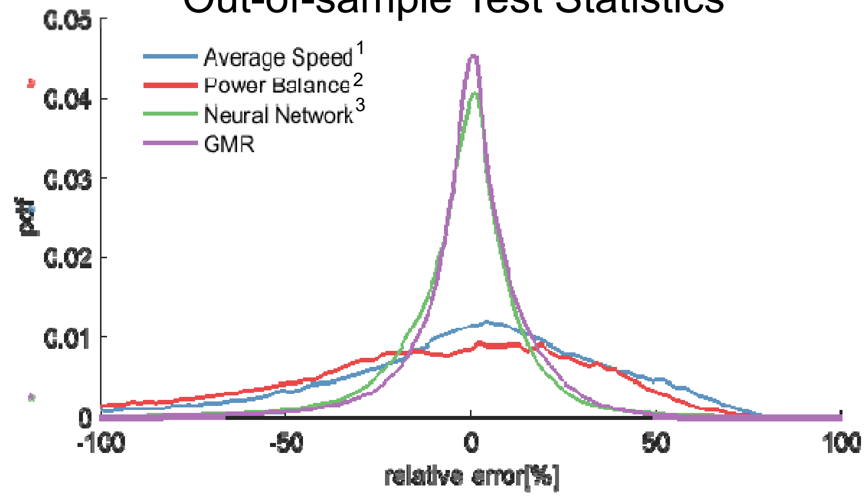
Trip Destinations

Model Performance

- Model: Gaussian Mixture Regression (GMR)
- Input variables

Initial and Final Speed
Average Speed
Elevation Change
Link Length
Speed Limit

Out-of-sample Test Statistics

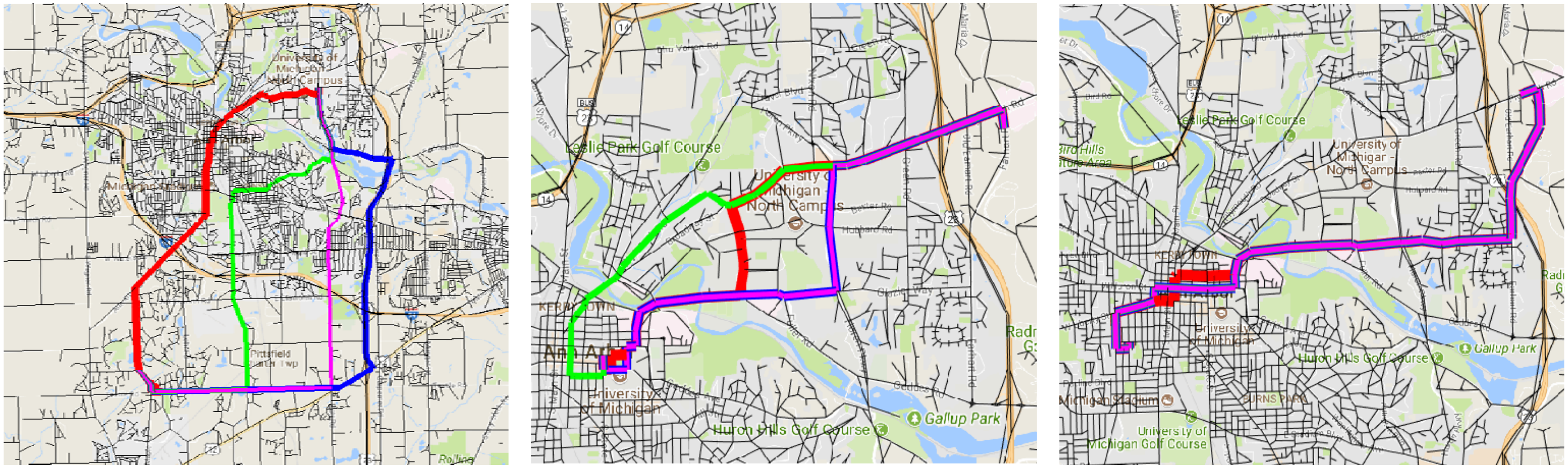


Model	R^2	MAPE [%]
Average speed model	0.77	37.63
Power balance model	0.86	46.22
Neural Network	0.98	15.60
GMR	**0.98**	**10.08**

1. K. Boriboonsomsin, M. Barth, S. Member, W. Zhu, and A. Vu, "ECO-Routing Navigation System based on Multi- Source Historical and Real-Time Traffic Information," *Network*, vol. 13, no. 4, pp. 1694–1704, 2012
2. J. Kwon, A. Rousseau, and P. Sharer, "Analyzing the uncertainty in the fuel economy prediction for the EPA MOVES binning methodology," SAE Int., 2007.
3. W. Zeng, D. Candidate, T. Miwa, and T. Morikawa, "Application of machine learning and heuristic k-shortest path algorithm to eco-routing problem with travel time constraint," pp. 1–18, 2016

Routing Results

- **Computation Time**: 13 s on Computer with Intel Core i7 and 16 G RAM

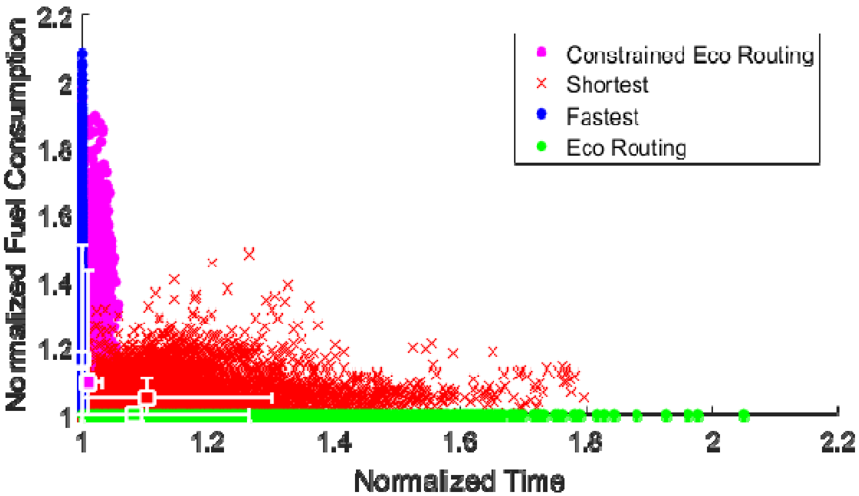


Shortest Route | Eco Route
Fastest Route | Constrained Eco Route

- **Frequently traveled OD**: 3031 pairs with 123 destinations and 80 origins
- **Eco Routing**
  - 21% same as fastest
  - 22% same as shortest
- **Constrained Eco Routing**
  - 48% same as fastest
  - 23% same as shortest

Routing Results

- **Constrained Eco Routing v.s. Fastest Routing**
  - Max fuel saving 51.8%, max time increase 6.48%
  - Expected fuel saving 5.16%, expected time increase 0.91%
- **Eco Routing v.s. Fastest Routing**
  - Max fuel saving 51.96%, max time increase 105.06%
  - Expected fuel saving 13.85%, expected time increase 8.40%
- **Expected performance:** estimated with OD pair frequency



	Expected Fuel consumption [kg]	Expected Travel Time [s]
Shortest	0.4809	611.37
Fastest	0.5312	554.45
Eco-routing	0.4576	601.04
Constrained eco-routing	0.5038	559.49

University of Michigan · Argonne National Laboratory · Idaho National Laboratory

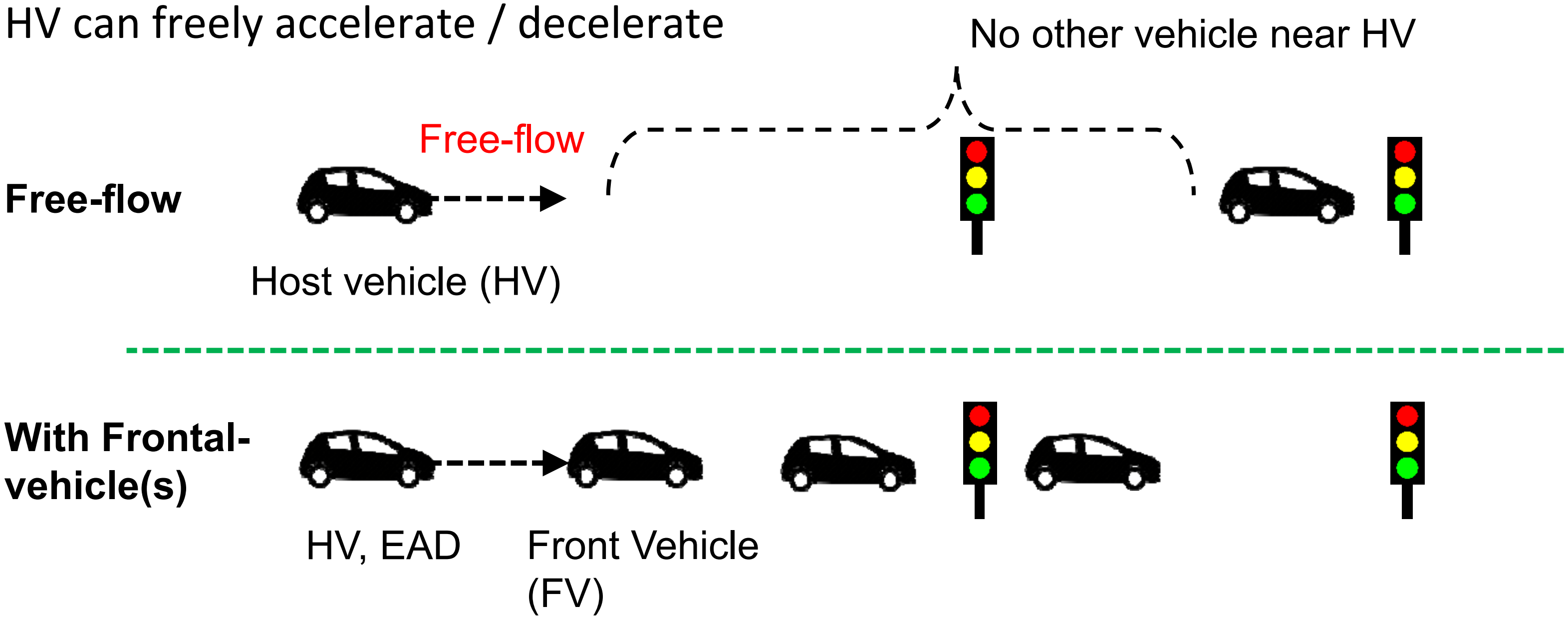
Technical Backup:
Case Study 2: Eco-approach and departure ('EAD') at Signalized Intersections Using Ann Arbor Data

1. Introduction : EAD Scenarios

[Single vehicle (Free-flow)]

No other vehicle near the host vehicle (HV).

HV can freely accelerate / decelerate



[Multiple vehicles (Front-vehicle)]

There is a frontal vehicle (FV) which constrains the motion of HV

2. EAD Problem Formulation

- Described as an optimization problem of **minimizing cost function J**
- Cost function J = **Fuel Consumption, Travel Time, Comfort**

$$\boxed{\min_{u} J = \int_{t_0}^{t_f} J(t)\, dt}$$

Components of the optimization problem	
Transitional Cost	Fuel Consumption
	Travel Time
	Riding Comfort
Hard Constraints	Red Lights Violation
	Speed Limit Violation
	Acceleration & Brake Limit
	Synchronizing End Speed for Fair Comparison
	Safety Constraint Violation (Front Vehicle case)
Initial & Final Conditions	Initial & Final position and speed
System Dynamics	$Ma = F - Mgf cos\theta - 0.5\rho C_d A(v + v_w)^2$

- Method : Dynamic Programming to find the global optimal solution

2. Dynamic Programming Simulation Details

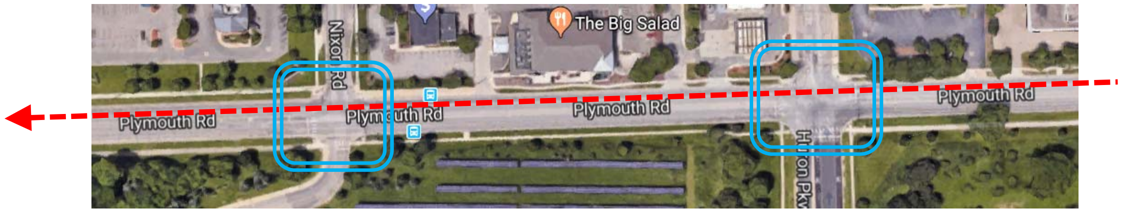
- Cost function is the weighted sum of **Fuel Consumption, Travel Time, Comfort**
- Given the hard constraints, the results (Fuel and Time savings) depend on w_f, w_{t_End}, $w_{SpdChange}$
- Details of Dynamics Programming Weights

Name of the weights		(1) WeightSet1 'Fuel-optimal'	(3) WeightSet2 'Fuel-saving'	(4) WeightSet3 'Time-saving'	(6) WeightSet4 'Time-optimal'
Stage Cost	w_f, Fuel	100	10		0
	w_{t_End}, End Time	0	0.2	1.0	100.0
	$w_{SpdChange}$, Comfort(SpdChange)	0	1		0
Hard Const-raints	End Speed Sync	$v(t_f) < v_{BSM} - v_\in$ or $v(t_f) > v_{BSM} + v_\in$			
	Invalid Speed	$v < 0$ *or* $v >$ *speed limit*			
	Final Location	$\mathrm{d}(t_f) < d_f$			
	Red Lights Violation	$d(t_i) \in [d_{node} - d_\in, d_{node} + d_\in,]$, $t_i \in t_{red}$			
	Turning Speed Violation	$v_{turn} > 5\mathrm{mph}$			
	FV Safety Violation	TTC $< 2.0(\mathrm{s})$ or Range $< Range_{lb}$			

University of Michigan · Argonne National Laboratory · Idaho National Laboratory

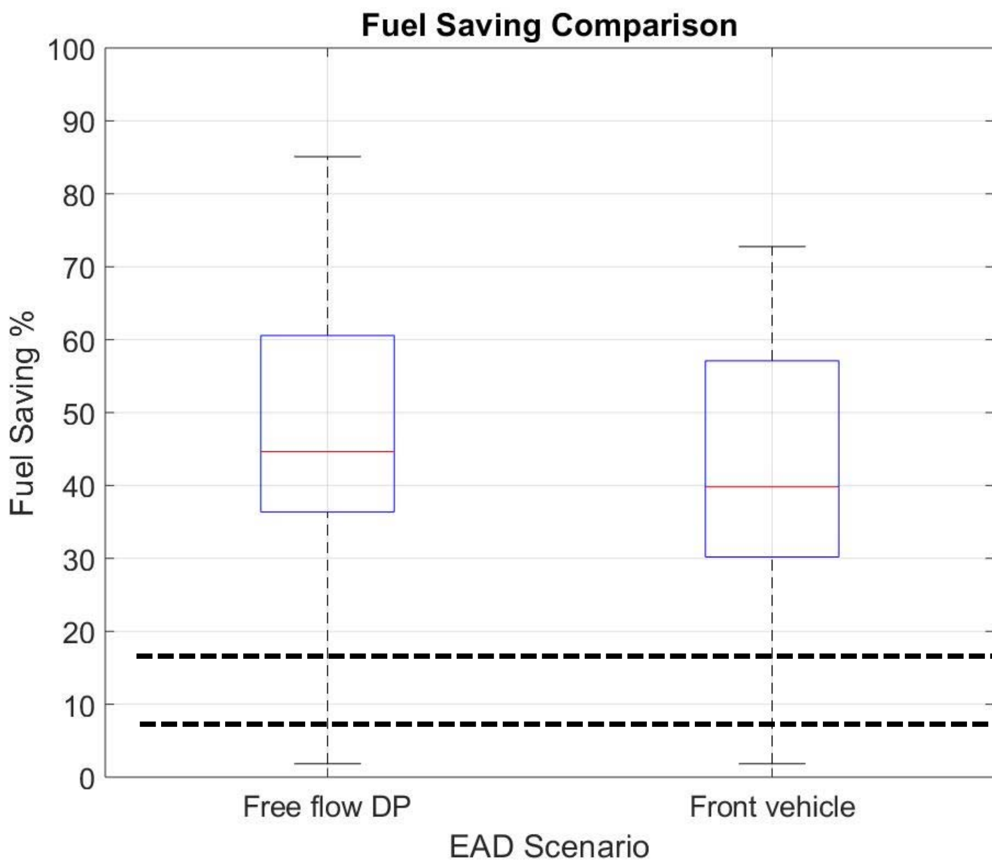
Studied 6 Intersections

- 1. Eastbound, 18003 -> 18004 (Fuller Cedarband -> Bonisteel)
- 2. Westbound, 18004 -> 18003 (Fuller Bonistell -> Cedarband)
- 3. Eastbound, 18013 -> 18014 (Plymouth Nixon -> Huron Pkwy)
- 4. Westbound, 18014 -> 18013 (Plymouth Pkwy -> Nixon)
- 5. Eastbound, 18006 -> 18007 (Fuller Fuller Court -> Huron High)
- 6. Westbound, 18007 -> 18006 (Fuller Huron High -> Fuller Court)
- All results are similar. Only one case reported below
  - From SPMD, **Human driving records at intersections** are reproduced
  - **Target Intersections** : Plymouth Road, Ann Arbor with 2 intersections

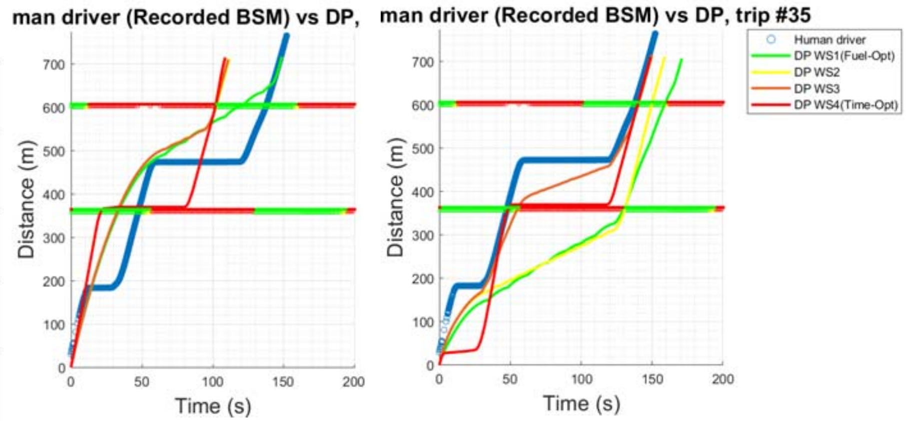


261 Trips recorded Westward, Through movement

3. Preliminary Result, Fleet Statistics



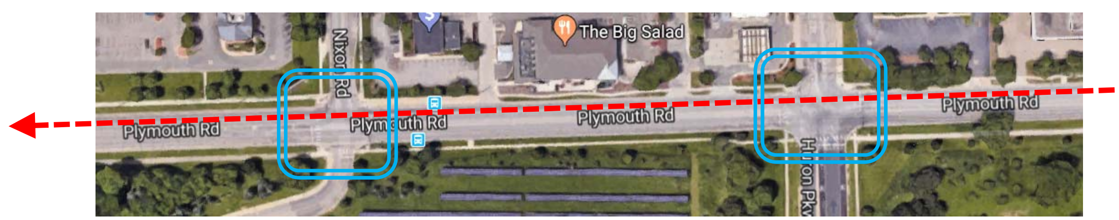
Free-flow   Ideal FV



Trip #35, 1005	BSM	WS1	WS2	WS3	WS4
Free-flow	47.1g	9.0g	11.0g	10.6g	63.5g
FV		14.3g	17.9g	19.8g	79.4g

17%, Glidepath (Altan, Barth et al, '17)

5-13%, AERIS (Capstone Report, '16)



UNIVERSITY OF MICHIGAN Argonne NATIONAL LABORATORY Idaho National Laboratory

4. Conclusion & Works in Progress

[Conclusion]

Eco-AND studied using real Ann Arbor trip data (real travel behavior). "What if" traffic signal information is used, for fuel saving in an ideal setting

But, EAD is only part of urban driving :

✓ **Does NOT reflect** fuel saving of the whole trip.

Free-flow EAD represent **the upper bound of fuel saving potential of EAD**

Ideal FV EAD offers estimation of the impacts of other vehicles/traffic to fuel saving

[Works in Progress]

Realistic FV case (With stochastic FV motion) : FV motion can be predicted from a Human FV model in the vicinity of the signalized intersections