Modeling and Optimization of Trip Level Energy Consumption and Charging Management for Connected Automated Electric Vehicles

Zonggen Yi, Ph.D.
Department of Advanced Vehicles and Energy Storage
Idaho National Laboratory

www.inl.gov

INL
Idaho National
Laboratory

Idaho National Laboratory – A Unique Capability for the Nation

Geography
- 890 square miles
- 1,350 miles of roads
- 21 miles of railroad lines
- 112 miles of electrical transmission and distribution lines

Infrastructure / Mission
- 4 reactors
- Nuclear and radiological facilities
- 2 spent fuel pools
- 400+ buildings
- 3 fire stations
- Mass transit system
- Explosive range
- Landfill
- Museum
- Significant security profile

Advancing Nuclear Energy
- Advanced reactor design and optimization
- Nuclear fuels and materials
- Fuel cycle technologies
- Light water reactor fleet sustainability

Enabling Clean Energy Systems
- Advanced transportation
- Environmental sustainability
- Clean energy
- Advanced manufacturing
- Biomass

Securing & Modernizing Critical Infrastructure
- Critical infrastructure protection and resiliency
- Nuclear nonproliferation
- Physical defense systems

INL Site

Specific Manufacturing Capability

Naval Reactors Facility

Idaho Nuclear Technology and Engineering Center

Materials and Fuels Complex

Advanced Test Reactor Complex

Critical Infrastructure Test Range Complex

Central Facilities Area

Research and Education Campus

Radioactive Waste Management Complex

INL Mission: *Discover, demonstrate and secure innovative nuclear energy solutions, clean energy options and critical infrastructure.*

Outline

- **Overview of Connected and Automated Electric Vehicles**

- Electric Vehicle Energy Consumption Modeling

- Energy Efficiency Driving Technologies

  – Eco-Driving

  – Eco-Routing

- Automatic Charging Decision Making for Connected and Automated Electric Vehicles

Connected and Automated Vehicles

- ## Levels of Automation
  - The SAE International definitions for levels of automation divide vehicles into levels based on "who does what, when."
  - **Fully automated, autonomous, or "self-driving" vehicles** are defined as "those in which operation of the vehicle occurs without direct driver input to control the steering, acceleration, and braking and are designed so that the driver is not expected to constantly monitor the roadway while operating in self-driving mode."

Level 0	The human driver does all the driving.
Level 1	An advanced driver assistance system (ADAS) on the vehicle can assist the human driver with either steering or braking/accelerating.
Level 2	An ADAS on the vehicle can control both steering and braking/accelerating under some circumstances. The human driver must continue to pay full attention ("monitor the driving environment") at all times and perform the rest of the driving task.
Level 3	An automated driving system (ADS) on the vehicle can perform all aspects of the driving task under some circumstances. The human driver must be ready to take back control at any time the ADS requests the human driver to do so. In all other circumstances, the human driver performs the driving task.
Level 4	An ADS on the vehicle can itself perform all driving tasks and monitor the driving environment – essentially, do all the driving – in certain circumstances. The human need not pay attention in those circumstances.
Level 5	An ADS on the vehicle can do all the driving in all circumstances. The human occupants are just passengers and need never be involved in driving.

The 5 levels of driving automation

For on-road vehicles — Human driver / Automated system

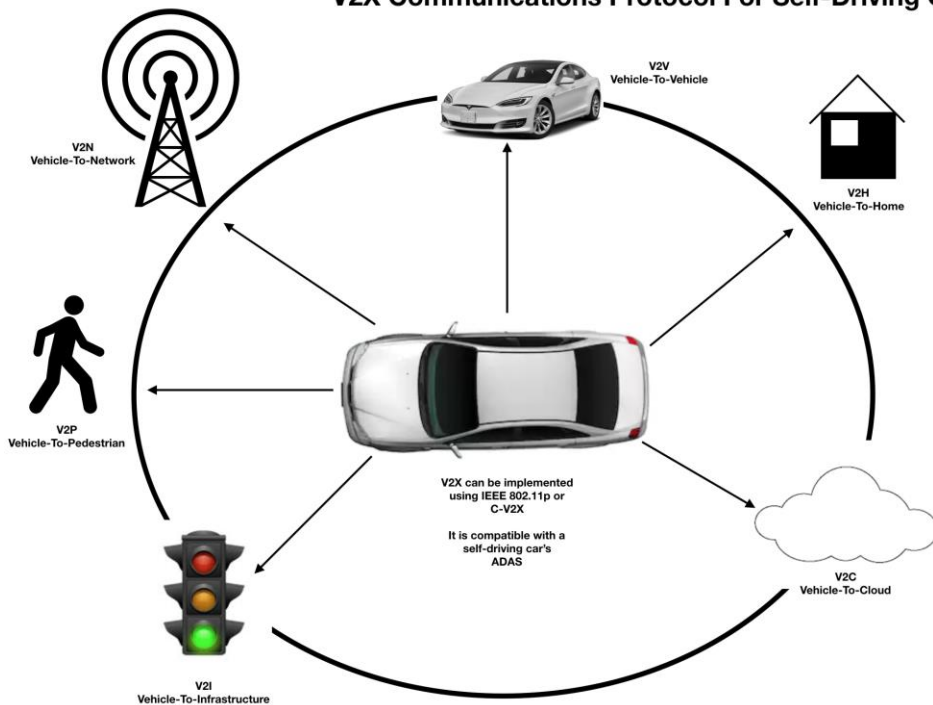|		Steering and acceleration/ deceleration	Monitoring of driving environment	Fallback when automation fails	Automated system is in control
0	NO AUTOMATION	Human driver	Human driver	Human driver	N/A
1	DRIVER ASSISTANCE	Human/System	Human driver	Human driver	SOME DRIVING MODES
2	PARTIAL AUTOMATION	System	Human driver	Human driver	SOME DRIVING MODES
3	CONDITIONAL AUTOMATION	System	System	Human driver	SOME DRIVING MODES
4	HIGH AUTOMATION	System	System	System	SOME DRIVING MODES
5	FULL AUTOMATION	System	System	System	System

Connected and Automated Vehicles

- **Connected Vehicles**
  - Connected vehicles are vehicles that use any of a number of different communication technologies to communicate with the driver, other cars on the road (V2V), roadside infrastructure (V2I), and the "Cloud" (V2C).
  - This technology can be used to not only improve vehicle safety, but also to improve vehicle efficiency and commute times.

V2I	V2V	V2C	V2P	V2X
Vehicle to Infrastructure	Vehicle to Vehicle	Vehicle to Cloud	Vehicle to Pedestrian	Vehicle to Everything

Source: http://autocaat.org/Technologies/Automated_and_Connected_Vehicles/

Source: https://medium.com/self-driving-cars/improving-self-driving-car-safety-and-reliability-with-v2x-protocols-1408082bae54

Source: https://phys.org/news/2018-06-demystifying-future-autonomous-vehicles.html

Connected and Automated Electric Vehicles
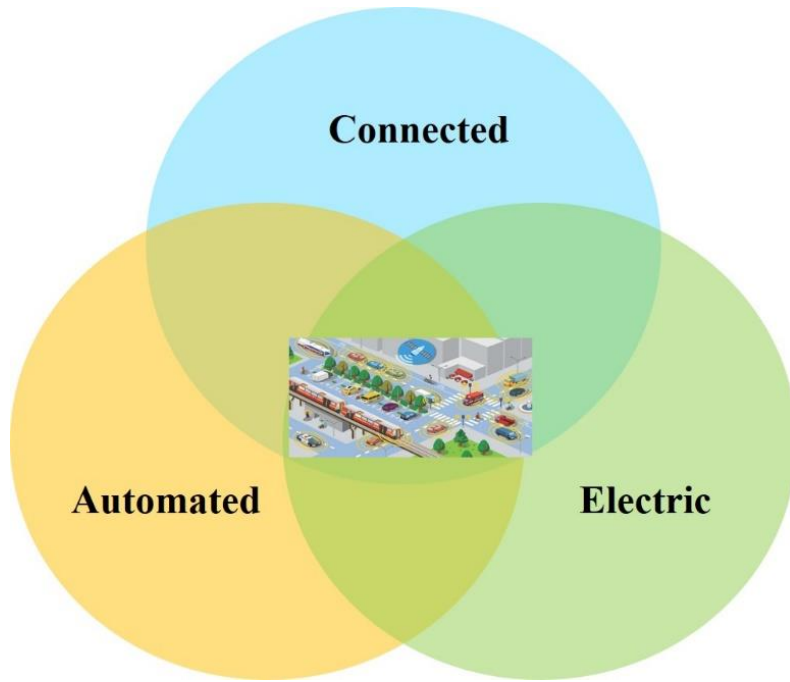
Convergence of the *Electric Propulsion Systems* and *Automated Vehicles*:

- EVs have inherent advantages when it comes to fuel savings and reducing the impact on the environment.

- It is easier for computers to drive electric vehicles.

- The lower operating cost of a battery-electric vehicle is a much bigger factor.

Major automakers' partnerships related to mobility, connectivity and driving automation

Source: https://www.cargroup.org/wp-content/uploads/2018/07/Impact-of-ACES.pdf

Applications From Connected Automated Vehicles

A variety of intelligent transportation system on highway, arterial and urban roads enabled by connected and automated vehicles

- Communication with other vehicles enables (**1**) augmented awareness, (**2**) platooning, and (**3**) cooperative maneuvers.

- (**4**): Communication with the infrastructure enables enhanced approach and departure to signalized intersections. Cloud connectivity enables access to databases, forecasts, and remote computations. On-board perception, localization and maps are fundamental to navigate in known and unknown environments.

- (**5**): Roadway sensors generate signal phase and timing (SPaT) and vehicle occupancy and speed (VOS) data, that can be stored in the cloud.

- (**6**): Other applications include coordination of grid charging, parking, road works

Source: Guanetti, Jacopo, Yeojun Kim, and Francesco Borrelli. "Control of connected and automated vehicles: State of the art and future challenges." *Annual Reviews in Control* (2018).

Overview of Energy Management for Connected Automated EVs

Electrified Drive Systems (PHEV,BEV,FEV)

Connected Vehicles (V2V, V2I, V2C, V2X, etc.)

Automated Driving Systems

Sustainable Transportation

Sustainable Mobility of Electric Vehicles

EV Energy Consumption Prediction Model

Energy Efficient Driving Technologies
- **Eco-Driving**
- **Eco-Routing**

Sustainable Charging Management
- **Charging Decision Making**
- **Sustainable Charging Infrastructure Planning**

Outline

- Overview of Connected and Automated Electric Vehicles

- **Electric Vehicle Energy Consumption Modeling**

- Energy Efficiency Driving Technologies

  – Eco-Driving

  – Eco-Routing

- Automatic Charging Decision Making for Connected and Automated Electric Vehicles

Electric Vehicle Energy Consumption Model and Prediction

- **Route Information**
- **Traffic Information**
- **Environmental Profile**

Energy Consumption Model and Prediction

- **Starting Location**
- **Energy Cost Constraint**
- **Routing Engine**
- **Traffic Information**
- **Environmental Profile**

Trip Level Energy Consumption Prediction

Reachable Range Estimation

Physical Based Modeling

Data Driven Modeling

Sources:
Zonggen Yi, Peter H. Bauer. "Energy Consumption Model and Charging Station Placement for Electric Vehicles." *Smartgreens*. 2014.
Zonggen Yi, Peter H. Bauer. "Effects of environmental factors on electric vehicle energy consumption: a sensitivity analysis." *IET Electrical Systems in Transportation* 7.1 (2016): 3-13.

Physical Based Methods for Energy Consumption Modeling

P_{bat} h_{bat} $\quad$ h_{conv} $\quad$ h_{contr} $\quad$ h_m $\quad$ h_{mp}

Battery → Power Converter → Motor Controller → Electric Motor → Mechanical Powertrain

P_{para} — Average Parasitic Power

Propulsion → ← Regenerative Braking
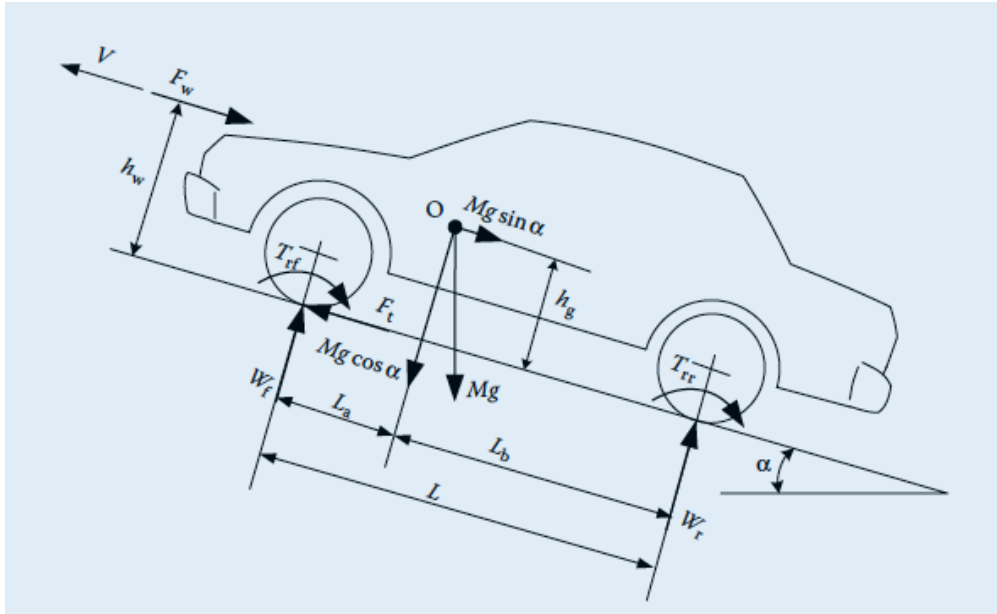
P_{wheel}

Wheels

Power Consumed at Wheels

$$P_{wheel}(t) = P_{air}(t) + P_{roll}(t) + P_{hill}(t) + P_{ac}(t)$$

Power Consumed at Battery

$$P_{bat}(t) = \frac{1}{\eta_{bat}} P_{bat}^{out}(t) = \frac{1}{\eta_{bat}} \frac{1}{\eta_{pt}} P_{wheel}(t)$$
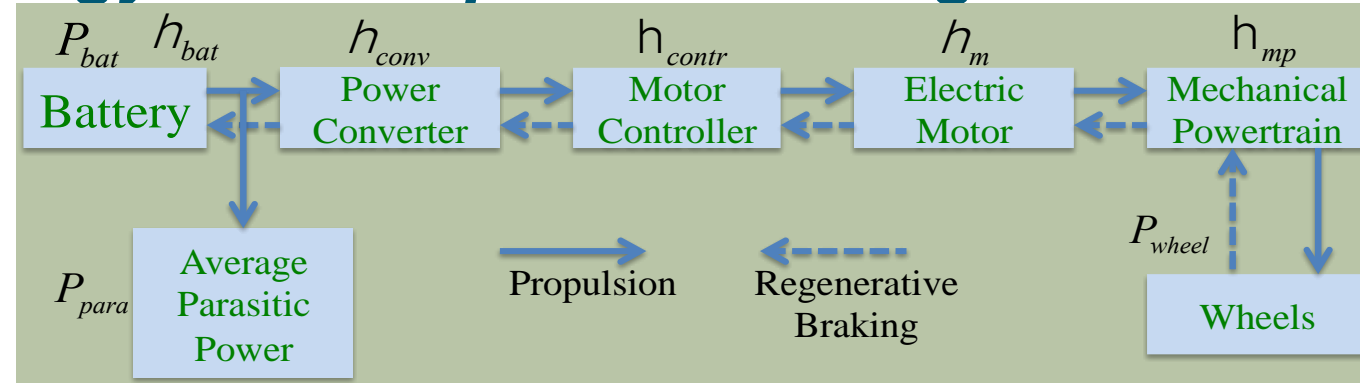
Air drag power

$$P_{air}(t) = \frac{1}{2} r C_d A (v(t) - w(t))^2 v(t)$$

Rolling resistance power

$$P_{roll}(t) = f_r(t)\left(1 + \frac{v(t)}{44.4}\right) Mg \cos(\partial(t)) v(t)$$

Acceleration power

$$P_{ac}(t) = Ma(t)v(t)$$

Hill climbing power

$$P_{hill}(t) = Mgv(t)\sin\partial(t)$$

- Mass: M
- Frontal area: A
- Drag coefficient: C_d
- Air density: ρ
- Wind speed: $w(t)$
- Rolling resistance: $f_r(t)$
- Road surface angle: $\alpha(t)$
- Vehicle speed: $v(t)$
- Acceleration: $a(t)$

Data Driven Methods for Energy Consumption Modeling

- Data-driven methods utilize machine learning models, and historical and real-time data that are collected from multiple resources to create the energy consumption models.

- The data may include the time-series data, such as, elevation, speed, acceleration and power consumption, and also include other static map and vehicle specification data, e.g. distance, trip run time, temperature, weight of loads, tire pressure, frontal area.

Hybrid Machine Learning Model
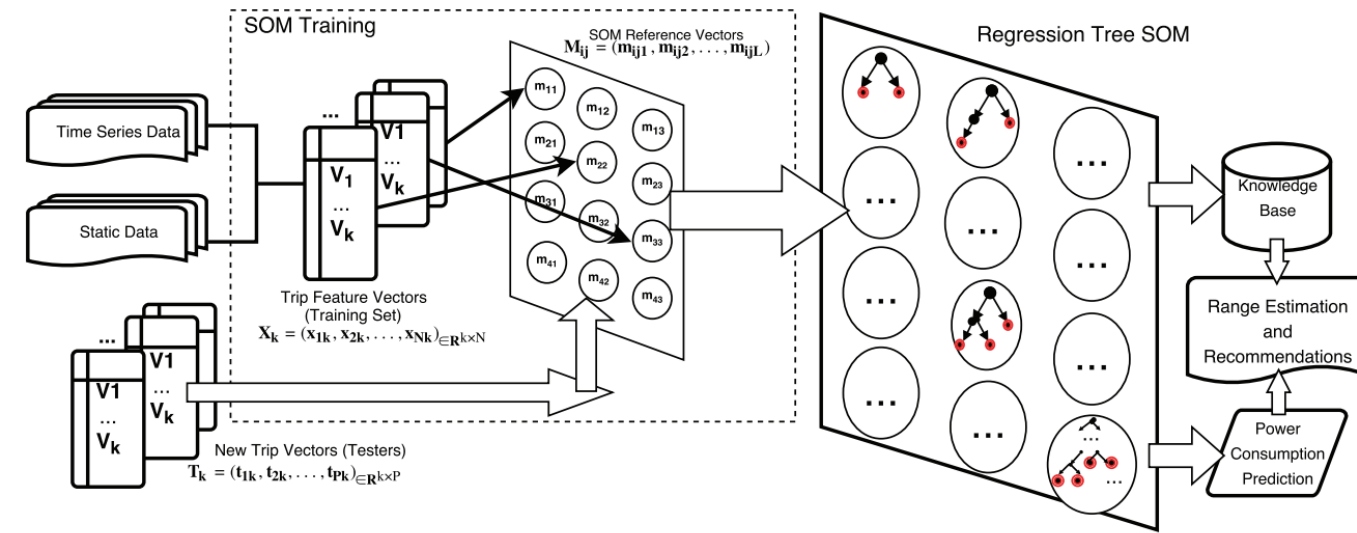
Multivariate Adaptive Regression Spline Approach
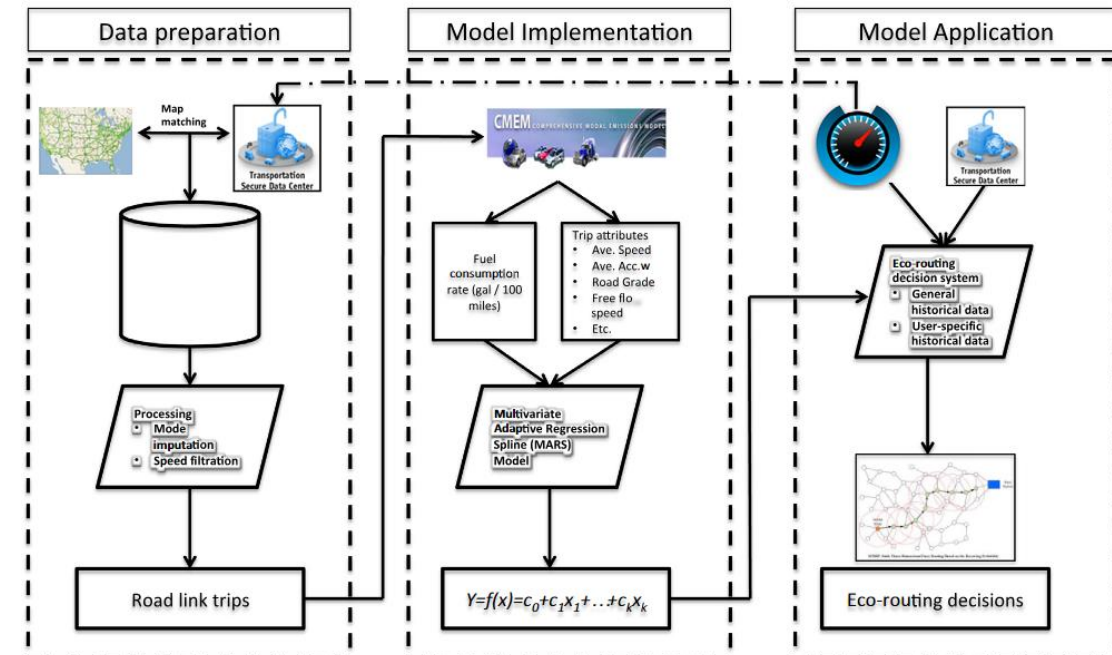
Source: B. Zheng, P. He, L. Zhao, and H. Li, "A hybrid machine learning model for range estimation of electric vehicles," in *Proc. Global Commun. Conf.*, Washington, DC, USA, Dec. 2016, pp. 1–6.

Source: Yuche Chen, et al. "Data-driven fuel consumption estimation: A multivariate adaptive regression spline approach." *Transportation Research Part C: Emerging Technologies* 83 (2017): 134-145.

References for EV Energy Consumption Modeling

- **Physical Based Methods**

1. J. G. Hayes, R. P. R. de Oliveira, S. Vaughan, and M. G. Egan. *Simplified electric vehicle power train models and range estimation*. In Vehicle Power and Propulsion Conference (VPPC), pages 1-5, Chicago, IL, USA, September 2011. IEEE.

2. R. Prins, R. Hurlbrink, and L. Winslow. *Electric vehicle energy usage modeling and measurement*. International Journal of Modern Engineering, 13(1):5-12, 2013.

3. K. Grewal and P. Darnell. *Model-based ev range prediction for electric hybrid vehicles*. In IET Hybrid and Electric Vehicles Conference(HEVC 2013), pages:1-6, London, November 2013.

4. C. Fiori, K. Ahn, and H. A. Rakha. *Power-based electric vehicle energy consumption model: Model development and validation*. Applied Energy, 168:257-268, 2016.

5. K. N. Genikomsakis and G.Mitrentsis, "*A computationally efficient simulation model for estimating energy consumption of electric vehicles in the context of route planning applications*," *Transp. Res. D, Transp. Environ.*, vol. 50, pp. 98–118, 2017.

6. Zonggen Yi, Peter H. Bauer. "*Effects of environmental factors on electric vehicle energy consumption: a sensitivity analysis*." *IET Electrical Systems in Transportation* 7.1 (2016): 3-13.

7. Zonggen Yi, Peter H. Bauer. "*Adaptive multiresolution energy consumption prediction for electric vehicles*." *IEEE Transactions on Vehicular Technology* 66.11 (2017): 10515-10525.

- **Data Driven Methods**

1. Y. Zhang, W.Wang, Y. Kobayashi, and K. Shirai. *Remaining driving range estimation of electric vehicle*. In International Electric Vehicle Conference (IEVC), pages: 1-7, Greenville, SC, USA, March 2012. IEEE.

2. P. Ondruska and I. Posner. *Probabilistic attainability maps: Efficiently predicting driver-specific electric vehicle range*. In Intelligent Vehicles Symposium Proceedings, pages 1169-1174, Dearborn, MI, USA, June 2014. IEEE.

3. P. Ondruska and I. Posner, "*The route not taken: Driver-centric estimation of electric vehicle range*," in *Proc. 24th Int. Conf. Autom. Planning Scheduling*, Portsmouth, U.K., Jun. 2014, pp. 413–420.

4. B. Zheng, P. He, L. Zhao, and H. Li, "*A hybrid machine learning model for range estimation of electric vehicles*," in *Proc. Global Commun. Conf.*, Washington, DC, USA, Dec. 2016, pp. 1–6.

5. H. Rahimi-Eichi and M.-Y. Chow, "*Big-data framework for electric vehicle range estimation*," in *Proc. 40th Annu. Conf. IEEE Ind. Electron. Soc.*, 2014, pp. 5628–5634.

6. R. Zhang and E. Yao, "*Electric vehicles' energy consumption estimation with real driving condition data*," *Transp. Res. D, Transp. Environ.*, vol. 41, pp. 177–187, 2015.

7. C. De Cauwer, J. Van Mierlo, and T. Coosemans, "*Energy consumption prediction for electric vehicles based on real-world data*," *Energies*, vol. 8, no. 8, pp. 8573–8593, 2015.

8. J. Wang, K. Liu, and T. Yamamoto, "*Improving electricity consumption estimation for electric vehicles based on sparse gps observations*," *Energies*, vol. 10, no. 1, pp. 129–140, 2017.

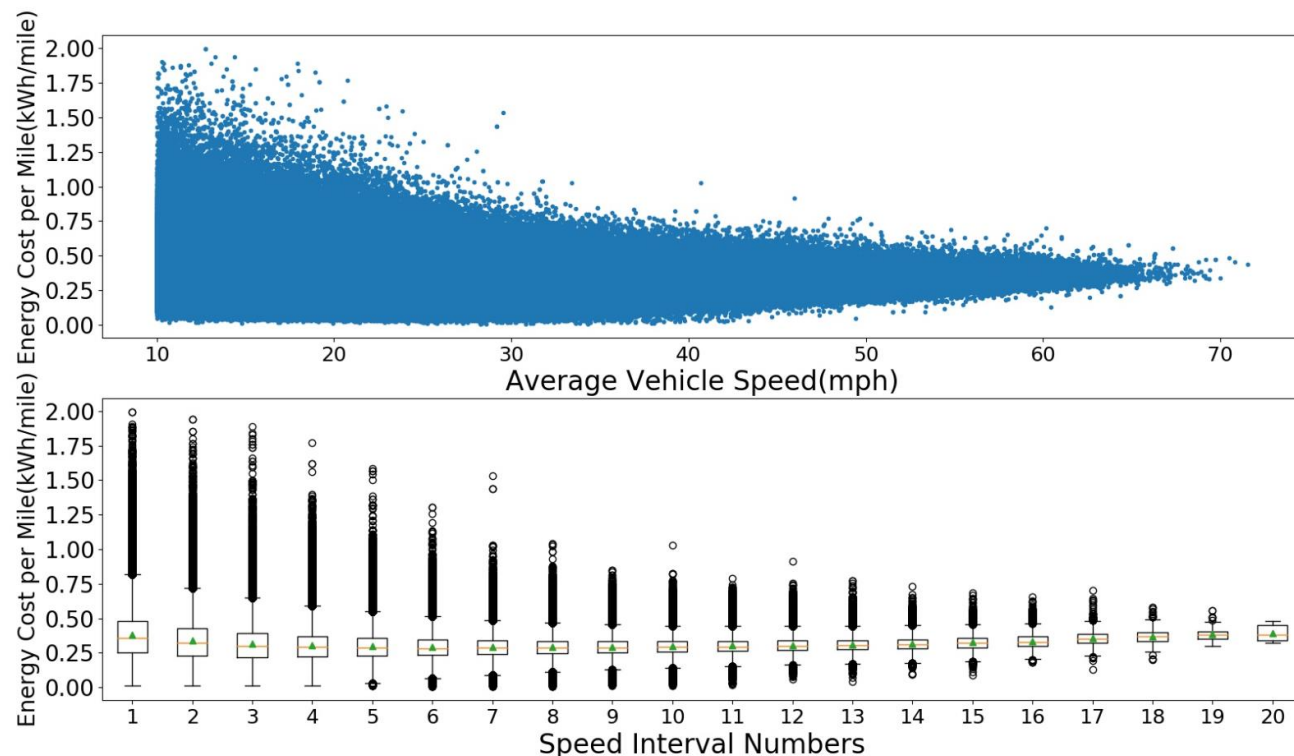# *Challenges of EV Energy Consumption Prediction*

- **Powertrain efficiency is determined by the operating conditions**
  - Vehicle Speed
  - Acceleration
  - Angle of Incline

- **Environmental effects on energy cost**
  - Wind speed
  - Rolling resistance
  - Parasitic power
  - Temperature
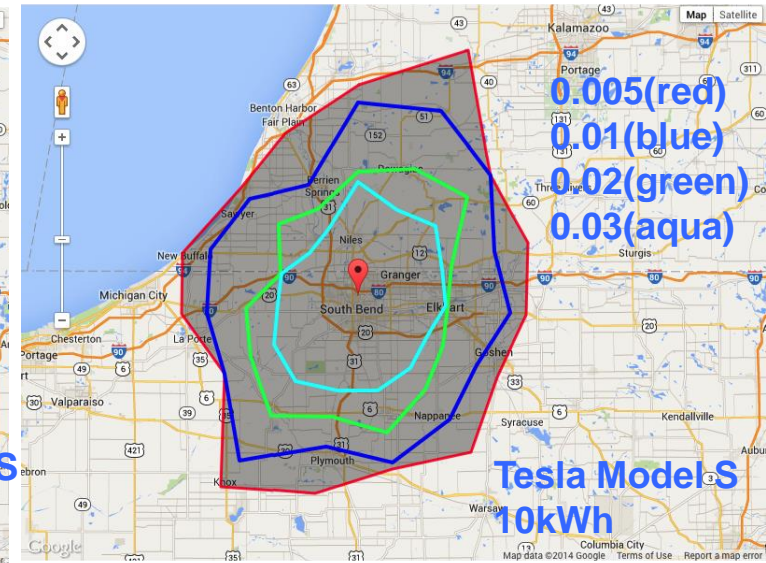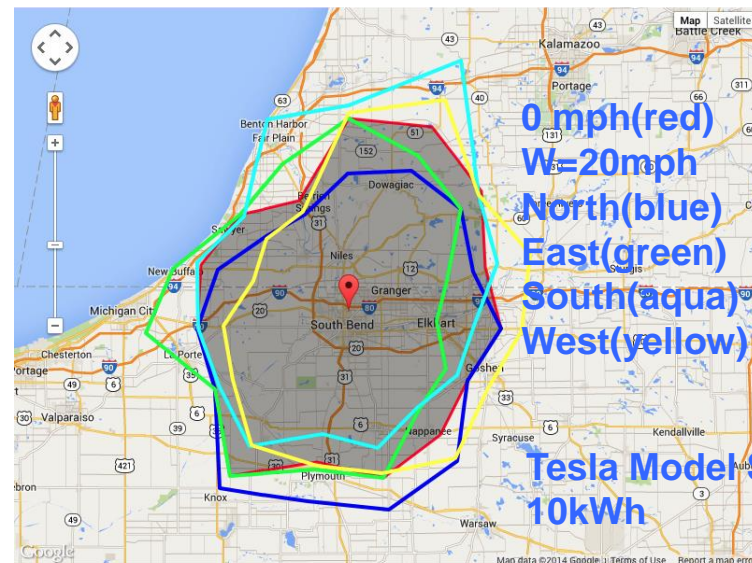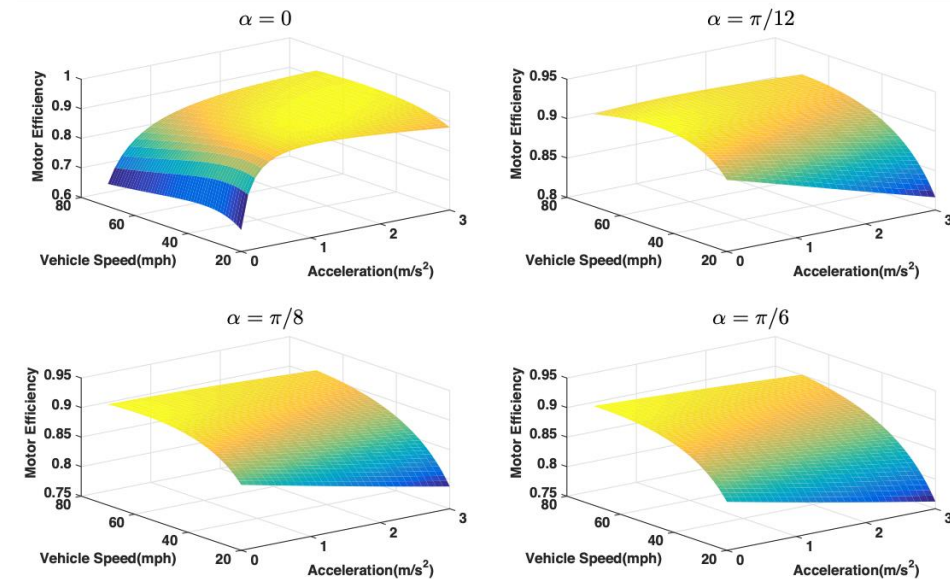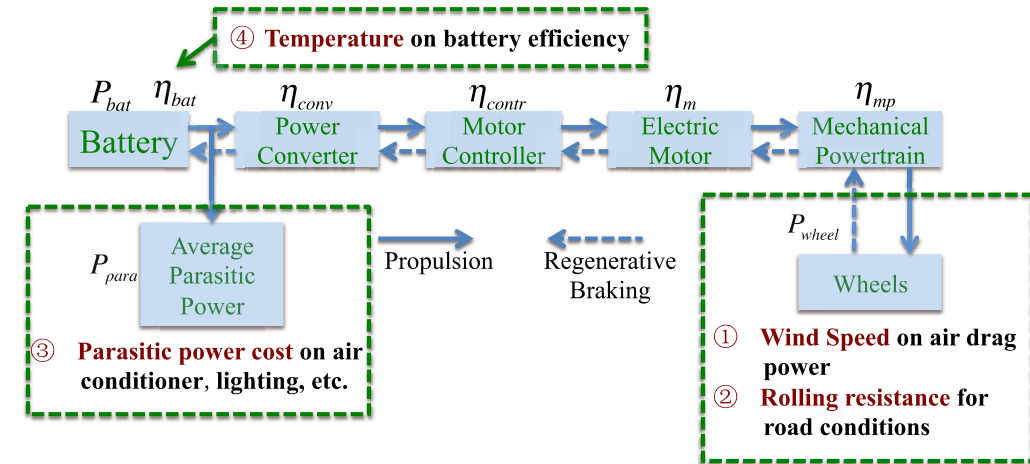
④ **Temperature** on battery efficiency

P_{bat} η_{bat} — η_{conv} — η_{contr} — η_m — η_{mp}

Battery → Power Converter → Motor Controller → Electric Motor → Mechanical Powertrain

P_{wheel}

P_{para} Average Parasitic Power — Propulsion — Regenerative Braking — Wheels

③ **Parasitic power cost** on air conditioner, lighting, etc.

① **Wind Speed** on air drag power
② **Rolling resistance** for road conditions

0 mph(red)
W=20mph
North(blue)
East(green)
South(aqua)
West(yellow)

Tesla Model S
10kWh

0.005(red)
0.01(blue)
0.02(green)
0.03(aqua)

Tesla Model S
10kWh

Source: Zonggen Yi, Peter H. Bauer. "Effects of environmental factors on electric vehicle energy consumption: a sensitivity analysis." *IET Electrical Systems in Transportation* 7.1 (2016): 3-13.

Challenges of EV Energy Consumption Prediction

- **Illustrations from Real World Historical Data**
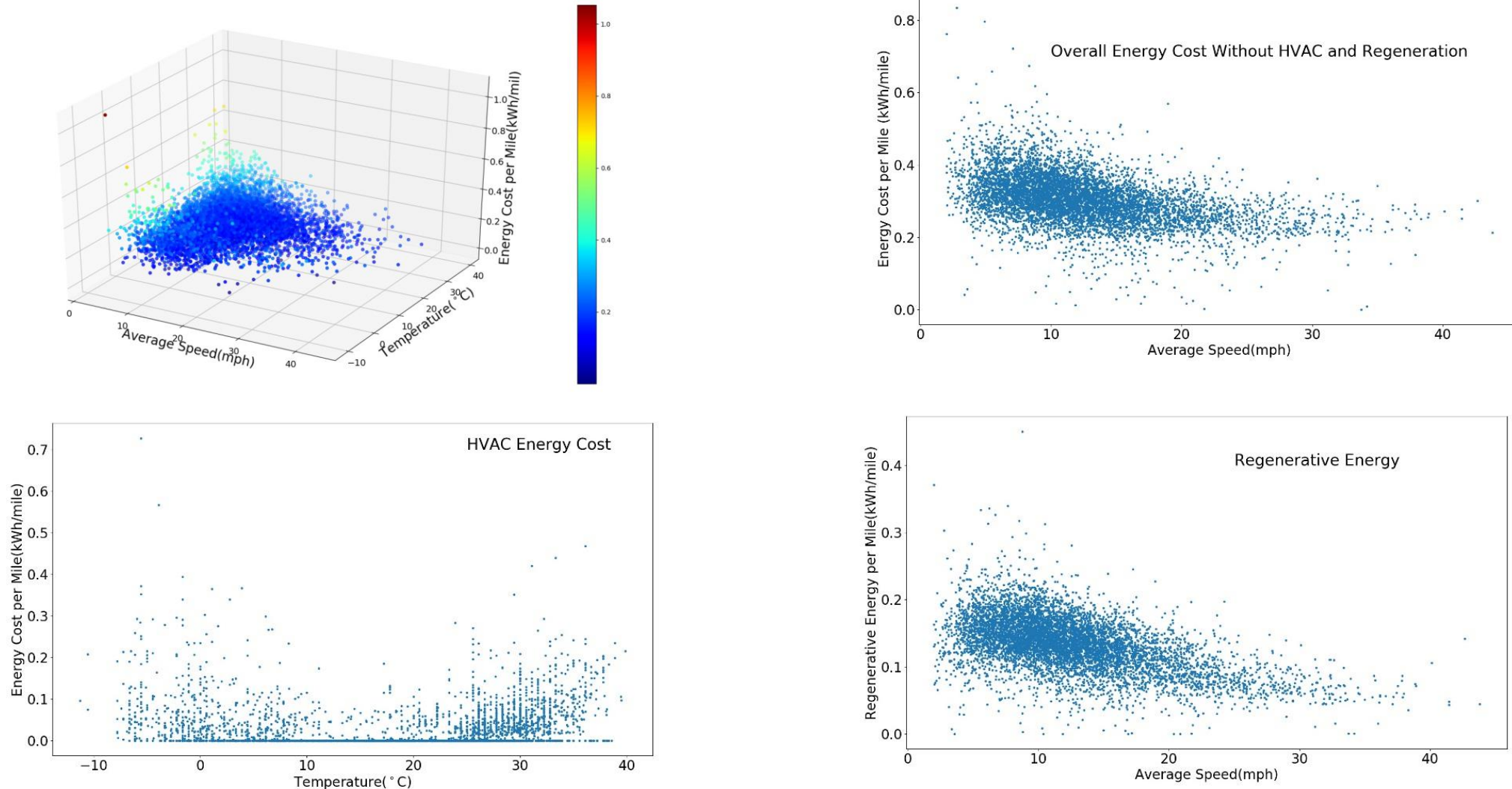
EV Energy Consumption Modeling Using Combined Method

- **Energy cost per mile (kWh/mile) distribution**

Source: Zonggen Yi, Matthew Shirk. "Data-driven optimal charging decision making for connected and automated electric vehicles: A personal usage scenario." *Transportation Research Part C: Emerging Technologies* 86 (2018): 37-58.

- **A stochastic model for Nissan Leaf**
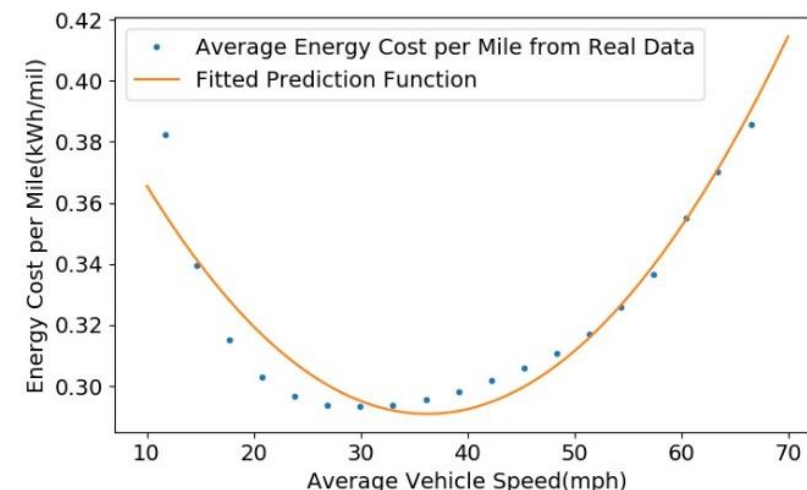
$$F_{mp}(v) = 0.00011v^2 - 0.00786v + 0.43340$$
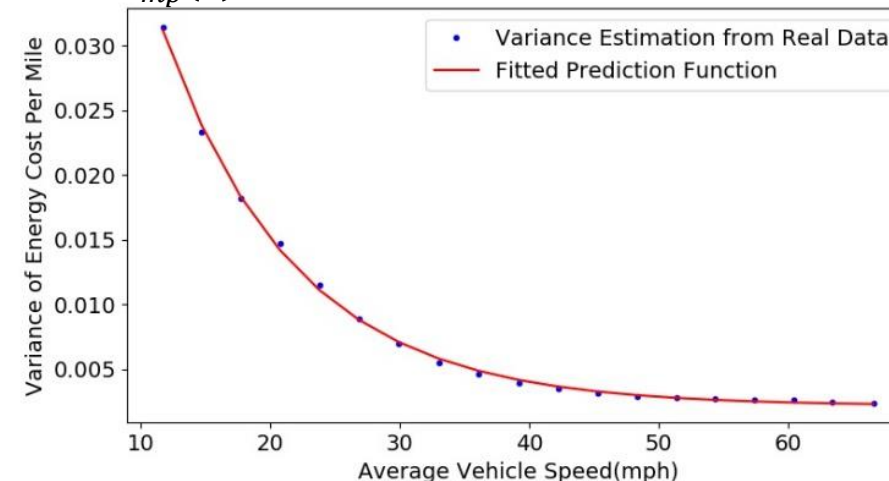
$$F_{vp}(v) = 0.09073e^{0.09736v} + 0.00219$$

EV Energy Consumption Modeling Using Combined Method

- **Multiple Channels Prediction Model and Real-time Update**
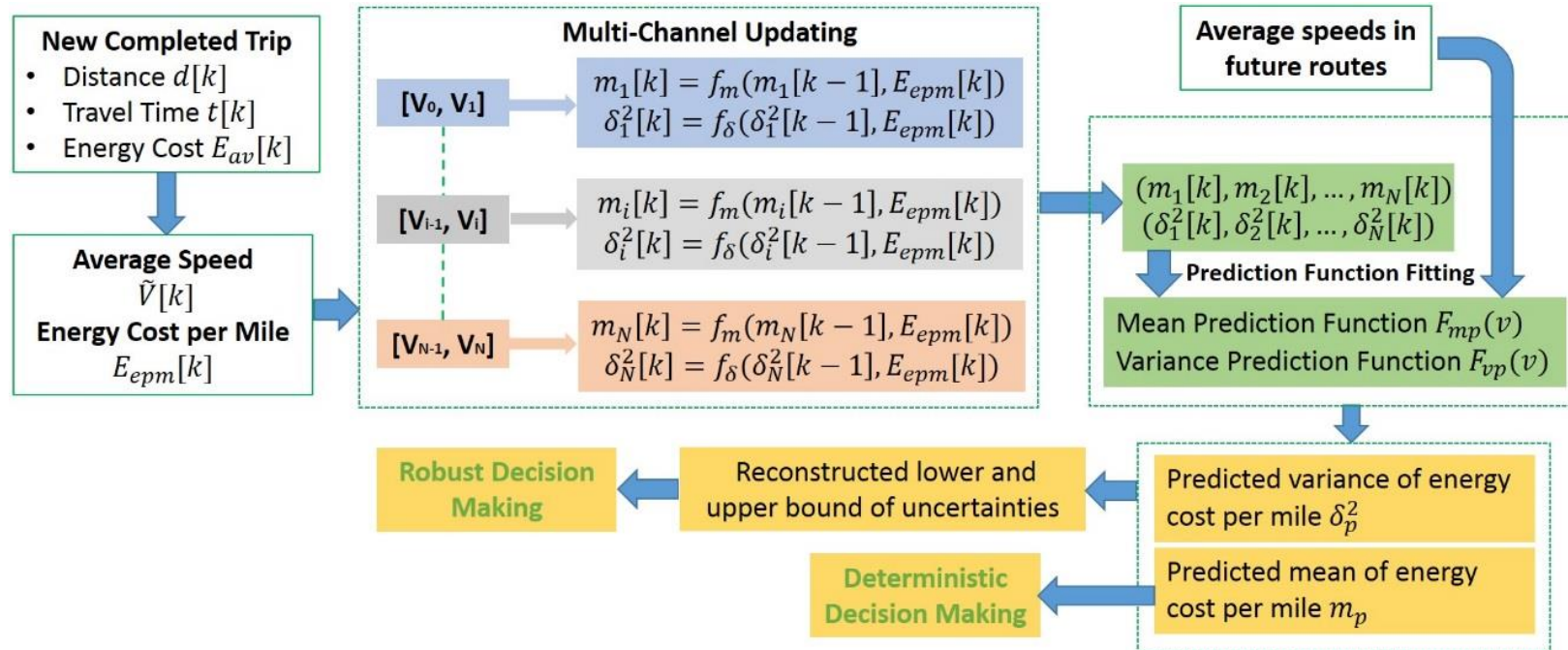
Requirement for promising EV energy consumption modeling

✓ *Combined Physical based data-driven modeling* can provide a robust and feasible modeling approach.

✓ *Stochastic modeling* can provide the capability of modeling real-world uncertainties.

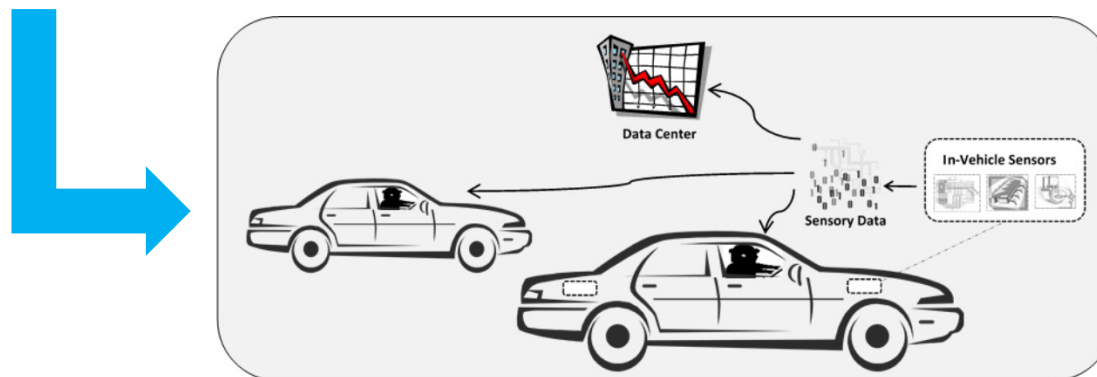✓ *Real-time updating* is necessary to handle the dynamics of real world traffic and other environmental conditions.

Opportunities of Connected EVs for Energy Consumption Prediction

Source: https://www.bourns.com/products/automotive/automotive-sensors

Source: https://www.neophotonics.com/sensors-for-autonomous-driving/

Vehicle as a Mobile Sensor

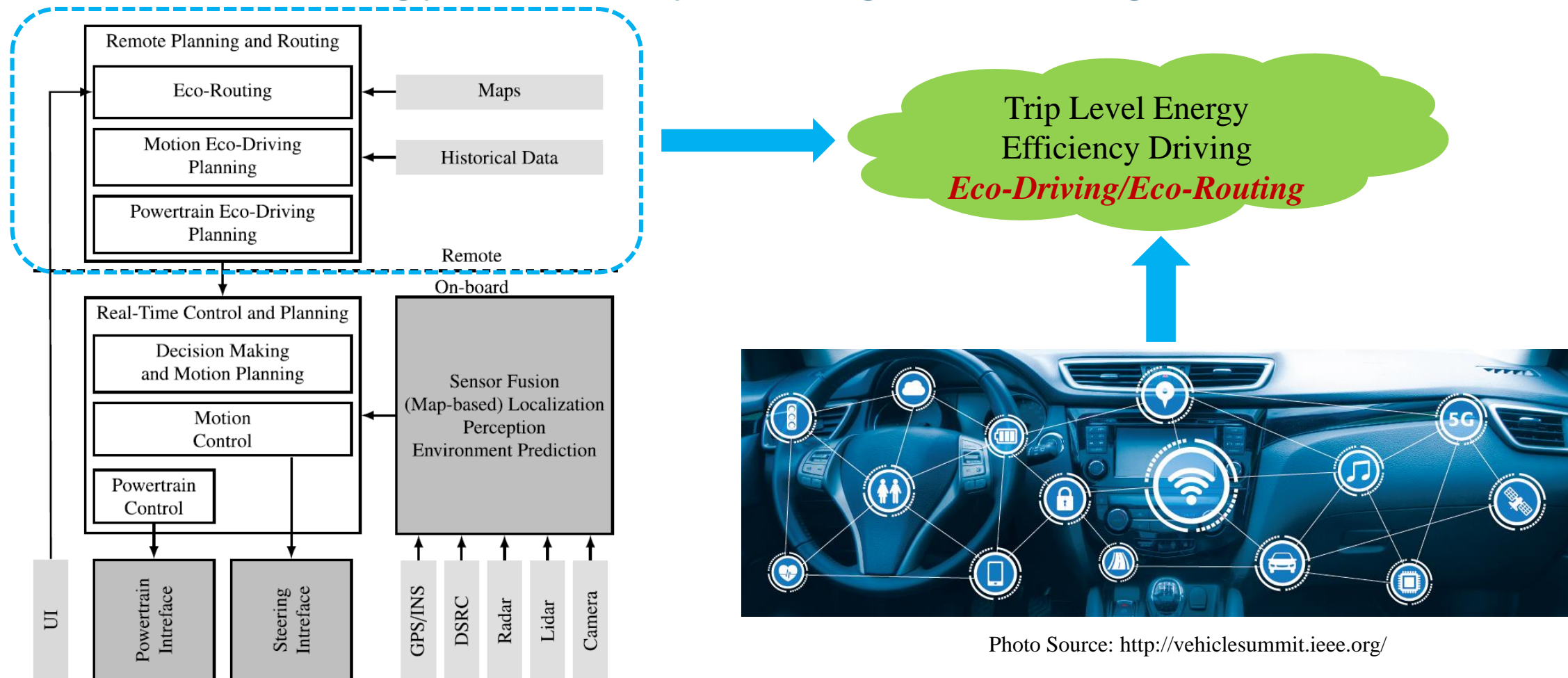| V2I	V2V	V2C	V2P	V2X
Vehicle to Infrastructure	Vehicle to Vehicle	Vehicle to Cloud	Vehicle to Pedestrian	Vehicle to Everything

Source: Sherin Abdelhamid, Hossam S. Hassanein, and Glen Takahara. "Vehicle as a mobile sensor." *Procedia Computer Science* 34 (2014): 286-295.

Outline

- Overview of Connected and Automated Electric Vehicles

- Electric Vehicle Energy Consumption Modeling

- **Energy Efficiency Driving Technologies**

  – **Eco-Driving**

  – **Eco-Routing**

- Automatic Charging Decision Making for Connected and Automated Electric Vehicles
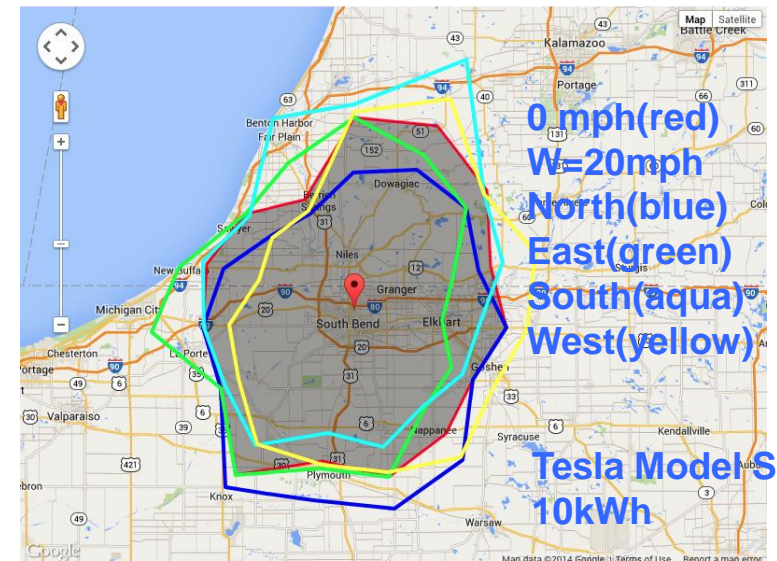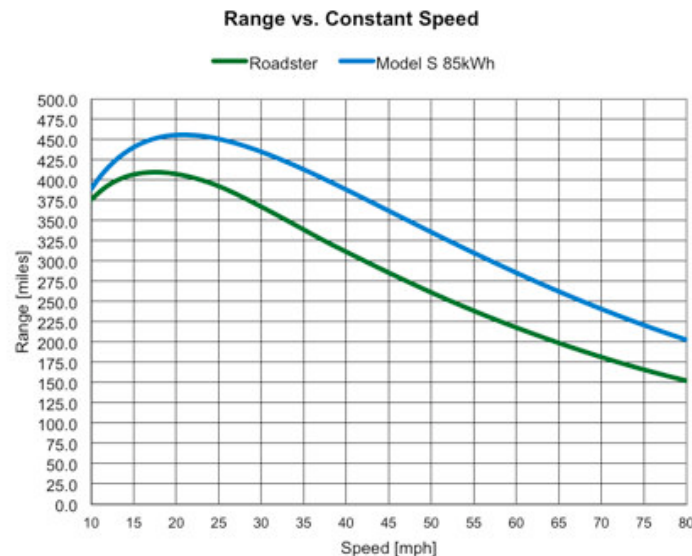
Overview of Energy Efficiency Driving Technologies

Remote Planning and Routing
- Eco-Routing ← Maps
- Motion Eco-Driving Planning ← Historical Data
- Powertrain Eco-Driving Planning

Remote

On-board

Real-Time Control and Planning
- Decision Making and Motion Planning
- Motion Control
- Powertrain Control

Sensor Fusion (Map-based) Localization Perception Environment Prediction

UI | Powertrain Intreface | Steering Interface

GPS/INS | DSRC | Radar | Lidar | Camera

Trip Level Energy Efficiency Driving
Eco-Driving/Eco-Routing

Photo Source: http://vehiclesummit.ieee.org/

Control and Optimization Architecture for Connected and Automated Vehicles

Source: Guanetti, Jacopo, Yeojun Kim, and Francesco Borrelli. "Control of connected and automated vehicles: State of the art and future challenges." *Annual Reviews in Control* (2018).

Eco-Driving Technologies in CAEVs

- **Eco-Driving** refers to the computation of a minimum-energy vehicle trajectory along a certain route.

- Eco-Driving exploits route information and long-term forecasts (such as road grade and traffic congestion) and accounts for constraints such as trip time and maximum velocity; vehicle stops and intersections are also considered on urban and arterial roads.

  - Energy efficient: EVs convert about 59%–62% of the electrical energy from the grid to power at the wheels. Conventional gasoline vehicles only convert about 17%–21% of the energy stored in gasoline to power at the wheels. (source: https://www.fueleconomy.gov/feg/evtech.shtml#end-notes)
  - Electric vehicles can have very different ranges under different vehicle speeds
  - Energy consumption is sensitive to environmental conditions

Range vs. Constant Speed

0 mph(red)
W=20mph
North(blue)
East(green)
South(aqua)
West(yellow)

Tesla Model S
10kWh

Eco-Driving Technologies in CAEVs

- **Optimal Speed Profile Design (Reference Cruising Velocity Generation)**
  - *Objective:* Optimal Speed Profile v(s) with regard to location
  - Position-Based Energy Consumption Model

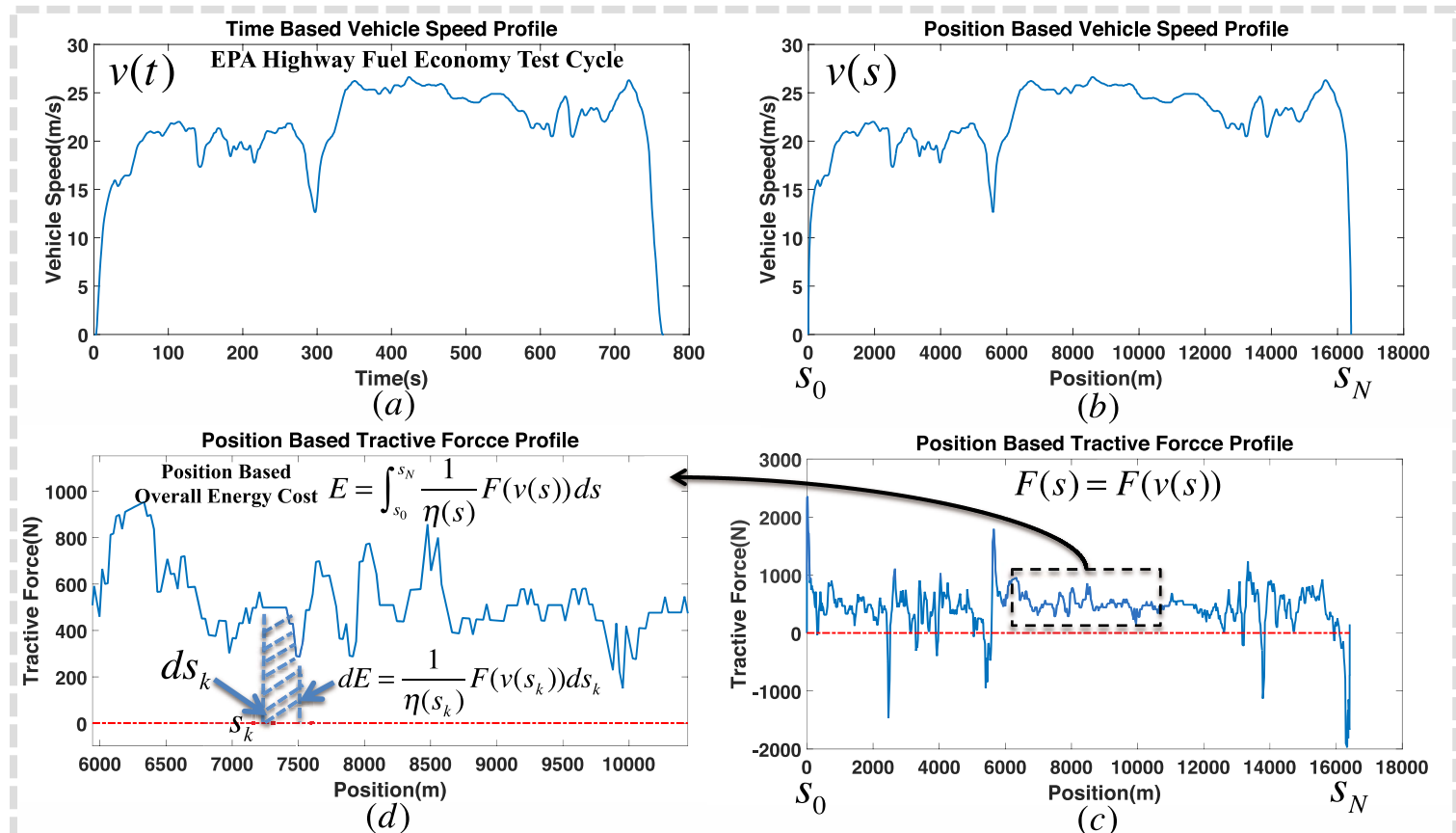➤ **Longitudinal Tire Force**

$$F(s) = F(v(s))$$
$$= F_{air}(s) + F_{ac}(s) + F_{hc}(s) + F_{rr}(s)$$

➤ **Position-Based Energy Cost**

$$E = \int_{s_0}^{s_N} dE = \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(s) ds$$
$$= \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(v(s)) ds$$

Source: Zonggen Yi, Peter H. Bauer. "Energy Aware Driving: Optimal
Electric Vehicle Speed Profiles for Sustainability in
Transportation." *IEEE Transactions on Intelligent Transportation
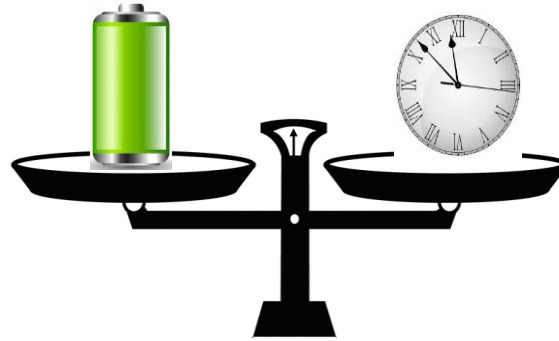Systems* 20.3 (2019): 1137-1148.

(a) Time Based Vehicle Speed Profile — EPA Highway Fuel Economy Test Cycle — $v(t)$

(b) Position Based Vehicle Speed Profile — $v(s)$

(c) Position Based Tractive Force Profile — $F(s) = F(v(s))$

(d) Position Based Tractive Force Profile — Position Based Overall Energy Cost $E = \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(v(s)) ds$ — $dE = \frac{1}{\eta(s_k)} F(v(s_k)) ds_k$

Eco-Driving Technologies in CAEVs

- **Optimal Speed Profile Design**

| Minimum Energy Cost with Time Cost Constraint(MECTC) | Minimum Time Cost with Energy Cost Constraint(MTCEC) |

$$\underset{v(s)}{\text{Min}} \quad \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(v(s)) ds$$

$$\text{subject to} \quad v_{ll}(s) \leq v(s) \leq v_{lu}(s)$$

$$\int_{s_0}^{s_N} \frac{1}{v(s)} ds \leq t_0$$

$$\underset{v(s)}{\text{Min}} \quad \int_{s_0}^{s_N} \frac{1}{v(s)} ds$$

$$\text{subject to} \quad v_{ll}(s) \leq v(s) \leq v_{lu}(s)$$

$$\int_{s_0}^{s_N} \frac{1}{\eta(s)} F(v(s)) ds \leq E_0$$

Overall Energy Cost:

$$E = \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(s) ds = \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(v(s)) ds$$

Overall Time Cost:

$$t = \int_{s_0}^{s_N} \frac{1}{v(s)} ds$$

s: Location information $\eta(s)$: Overall powertrain efficiency

$F(v(s))$: Tractive force $v(s)$: Vehicle speed profile

$v_{ll}(s)$: Lower bound of vehicle speed $v_{lu}(s)$: Upper bound of vehicle speed

Eco-Driving Technologies in CAEVs

- **Eco Approaching and Departure**
  - Minimize travel time, reduce acceleration peaks, avoid idling at red lights, or directly minimize energy consumption

- **Methodologies**
  - Heuristic Algorithms
  - Dynamic Programming
  - Model Predictive Control
  - Genetic Algorithms
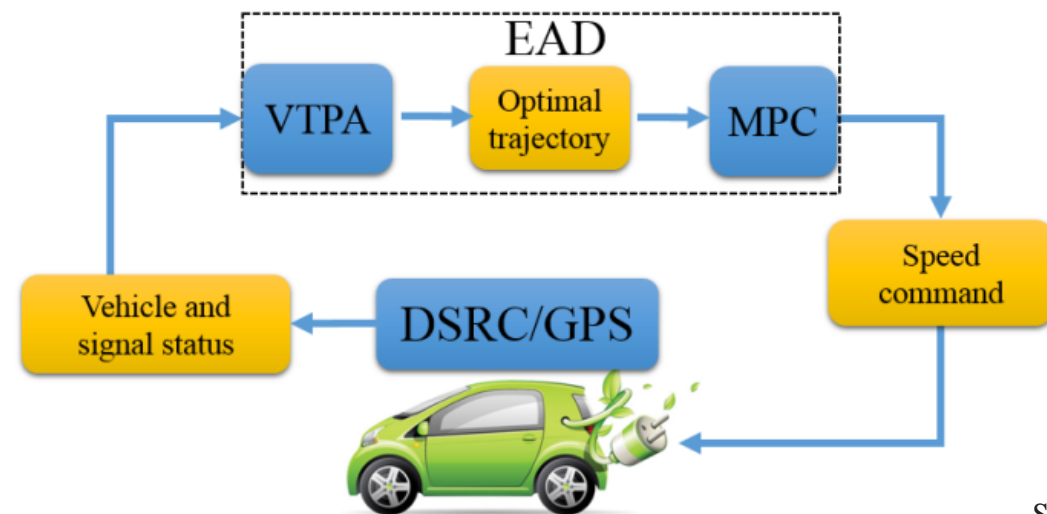
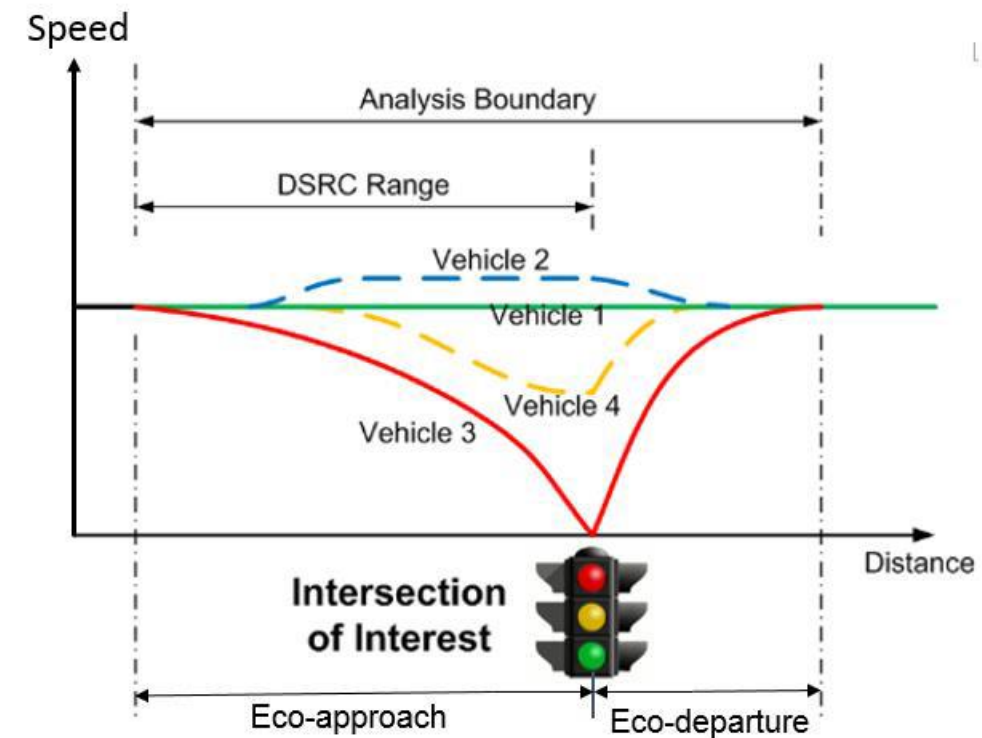**A system diagram of MPC-based EAD for EVs**

Illustration of different vehicle trajectories traveling across an intersection

Source: Xuewei Qi, Matthew J. Barth, Guoyuan Wu, Kanok Boriboonsomsin, and Peng Wang. "Energy impact of connected eco-driving on electric vehicles." In *Road Vehicle Automation 4*, pp. 97-111. Springer, Cham, 2018.

Eco-Driving Technologies in CAEVs

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1. Ozatay, E., Onori, S., Wollaeger, J., Ozguner, U., Rizzoni, G., Filev, D., et al. (2014). **Cloud-based velocity profile optimization for everyday driving: A dynamic-programming-based solution**. *IEEE Transactions on Intelligent Transportation Systems,15*(6), 2491–2505.

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Eco-Routing Technologies for CAEVs

- **Eco-Routing** aims to find a route that requires the least amount of fuel and/or produces the least amount of emissions for traditional vehicles.

- For electric vehicles with zero emission, **Eco-Routing** corresponds to finding the route with the minimum battery energy consumption.

- **Eco-Routing in electric vehicles has special features:**
  - The energy cost of a route segment can be negative due to regenerative braking, which can occur in two different ways: (a) downhill driving in a 3D route profile and (b) deceleration.
  - The recuperation of the kinetic and potential energy depends on the route choice as well as the characteristics of the power sources i.e. their capacity and powertrain efficiency

- **Methodologies**
  - **Dijkstra-like algorithms**: R. Abousleiman et al., 2014
  - **A* algorithms**: Y. Wang et al., 2013; A. Cela et al., 2014
  - **Optimization based techniques**: M. W. Fontana, 2013; O. Arslan et al., 2015, Zonggen Yi et al., 2018
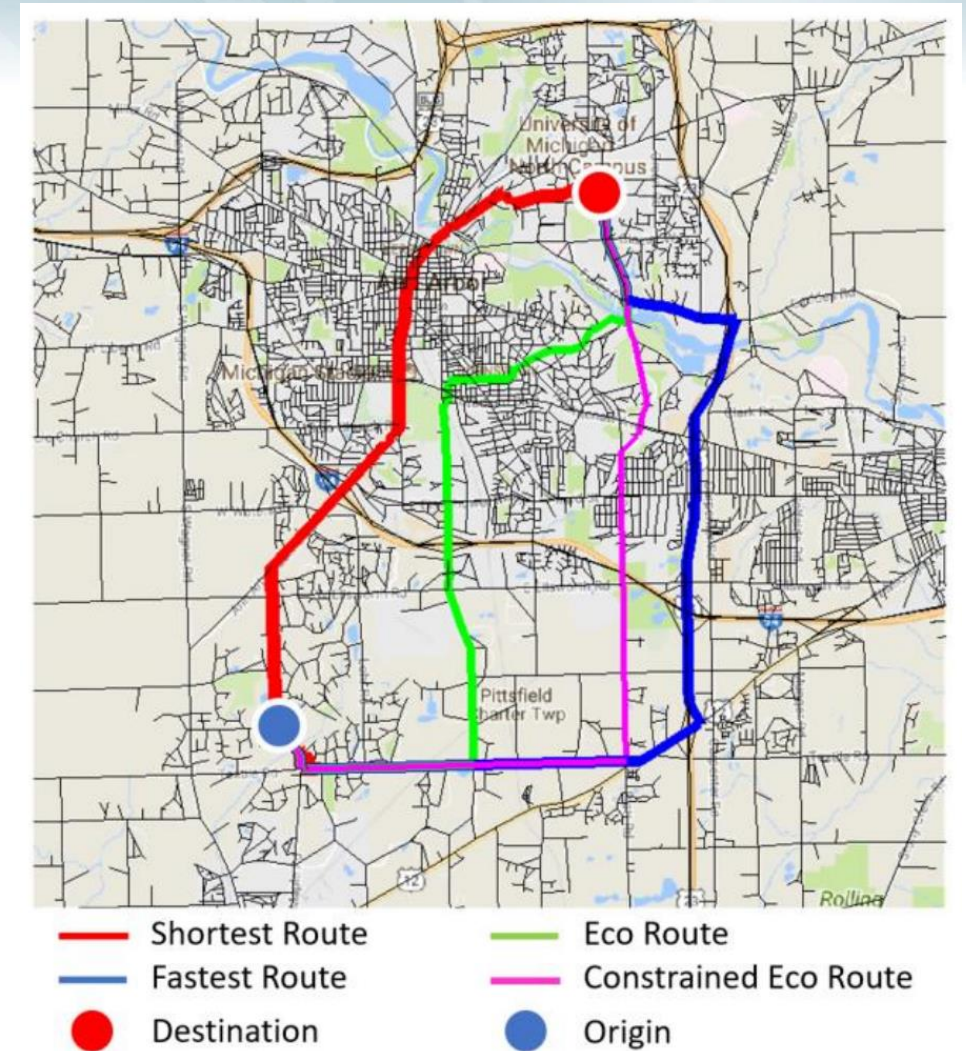
Sample path for shortest route, fastest route, eco route, and constrained eco route with routing cost estimated from posted speed limit
(Source: Huang, Xianan, and Huei Peng. "Eco-routing based on a data driven fuel consumption model." *arXiv preprint arXiv:1801.08602* (2018).)

Eco-Routing Technologies for CAEVs

- **Optimization Based Methods**

$$\min_{x_{ij}} \sum_{A_{ij} \in A_e} e_{ij} x_{ij}$$

$$s.t. \quad \sum_{j: A_{ij} \in A_e} x_{ij} - \sum_{j: A_{ji} \in A_e} x_{ji} = \begin{cases} 1 & if \ i \ is \ S \\ -1 & if \ i \ is \ D \\ 0 & otherwise \end{cases}$$

$$x_{ij} \in \{0,1\}, \forall \ A_{ij} \in A_e$$
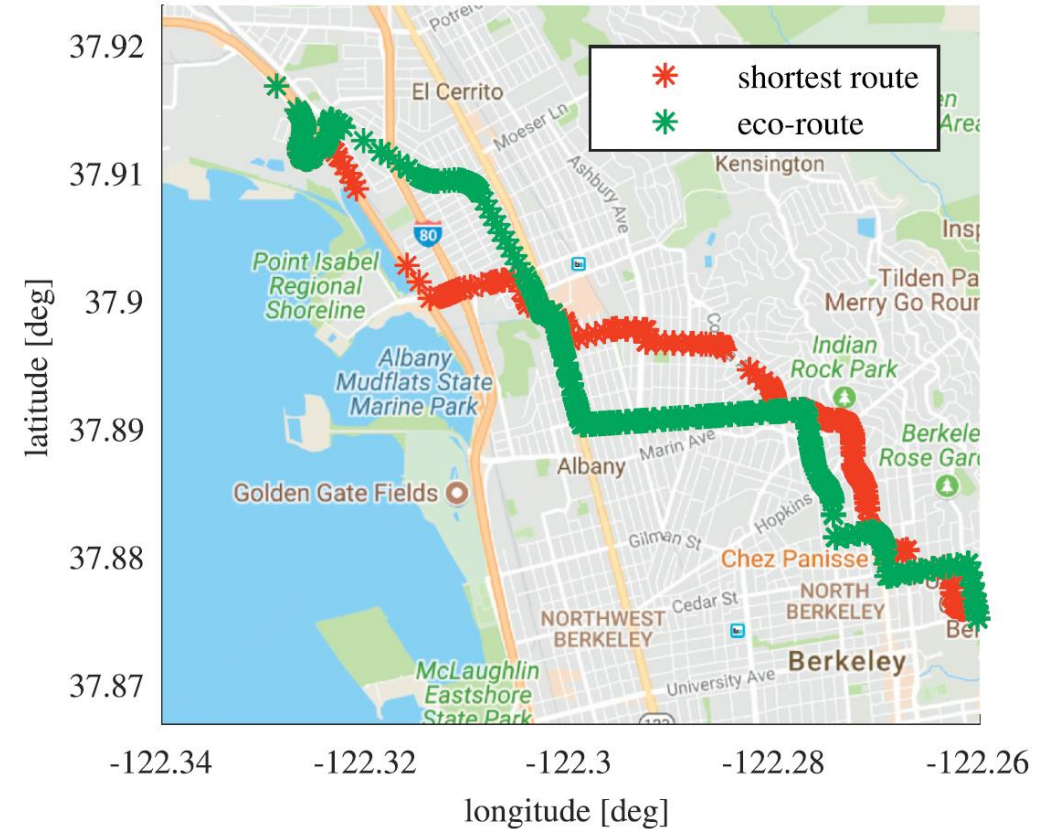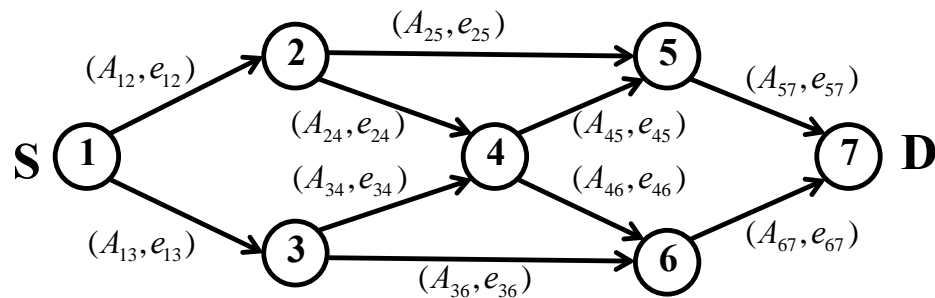
A comparison between the **minimum distance route** and the **minimum energy route**, for an origin and a destination in the Berkeley area: The minimum distance route is 9.72km long, and requires 4.23kWh according to a simple model of plug-in hybrid electric vehicle. The minimum energy route is 10.03km long, and requires 3.22kWh according to the same model.

Source: Guanetti, Jacopo, Yeojun Kim, and Francesco Borrelli. "Control of connected and automated vehicles: State of the art and future challenges." *Annual Reviews in Control* (2018).

Optimal Stochastic Eco-Routing Solutions

- **Stochastic Eco-Routing Model**
  - Minimize the mean value of overall energy cost for the selected route
  - Stochastic Integer Programming with Probability Constraint

$$\min_{x_{ij}} \quad E\left(\sum_{A_{ij} \in A_e} e_{ij} x_{ij} \right)$$

$$s.t. \quad P_r\left\{ \sum_{A_{ij} \in A_e} e_{ij} x_{ij} \leq \eta \right\} \geq p$$

$$\sum_{j:A_{ij} \in A_e} x_{ij} - \sum_{j:A_{ji} \in A_e} x_{ji} = \begin{cases} 1 & if \ i \ is \ S \\ -1 & if \ i \ is \ D \\ 0 & otherwise \end{cases}$$

$$x_{ij} \in \{0,1\}, \forall \ A_{ij} \in A_e$$
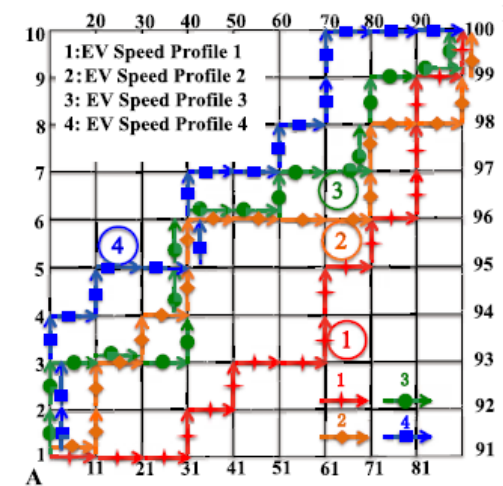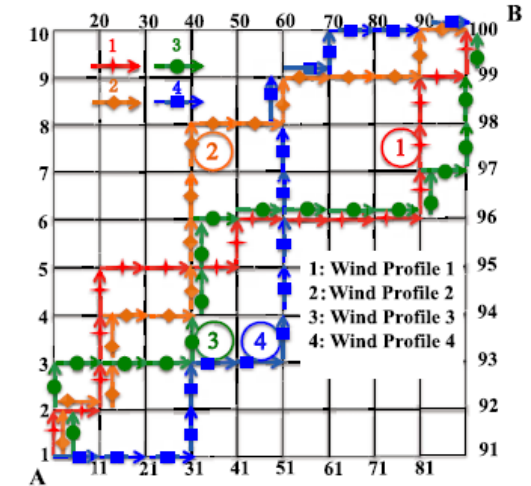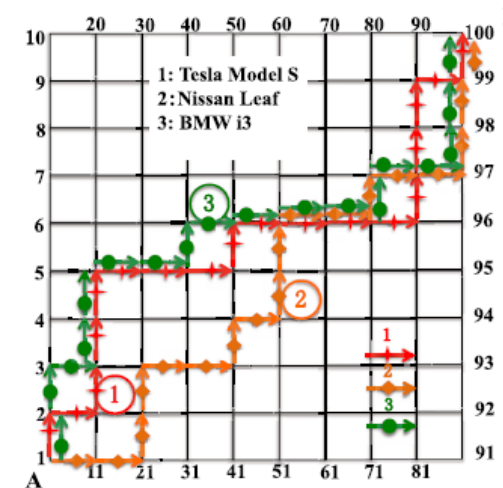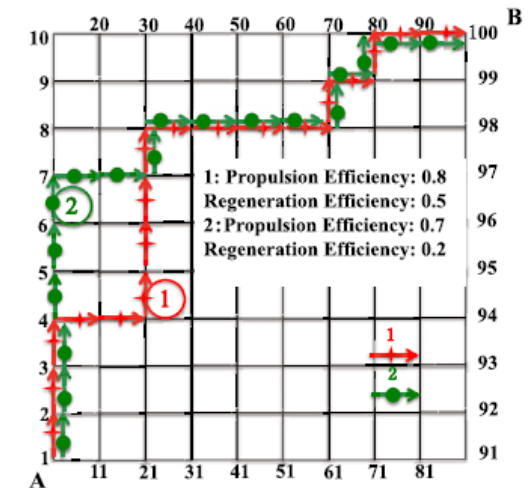
(a) Optimal routes with different vehicular speeds; (b) Optimal routes with different wind speeds; (c) Optimal routes with different EV types; (d) Optimal routes with different efficiencies

Source: Zonggen Yi, Peter H. Bauer. "Optimal stochastic eco-routing solutions for electric vehicles." IEEE Transactions on Intelligent Transportation Systems 19.12 (2018): 3807-3817.

(a) (b) (c) (d)

Eco-Routing Technologies for CAEVs

- **References**

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Challenges of Energy Efficiency Technologies in CAEVs

- **Challenges of Eco-Driving**

  – In optimal control formulations, traffic speed is easily included as an upper bound on the vehicle speed; however, its uncertainty is generally neglected, with effects that have not been investigated thus far.

  – Stop signs can also be included as state constraints in optimal control formulations; since they enforce a full vehicle stop, this approach essentially generates a multi-phase problem.

  – A stochastic optimization formulation for intersections with actuated signals should be considered. If the assumption of free flow on the road link is removed, forecasts of the traffic state (vehicle occupancy and speed, queue length) are required.

  – In electric and hybrid powertrains, avoiding vehicle stops may not always be the best policy: the combination of regenerative braking and engine on/off may affect significantly the optimal strategy.

Challenges of Energy Efficiency Technologies in CAEVs

- **Challenges of Eco-Routing**

    - Common pitfalls are model accuracy and uncertainty. The application of eco-routing to CAEVs seems promising in this regard: the on-board controls, removing to some extent the human driver from the loop, lead to more consistent energy consumption.

    - A direction that has been little investigated is the use of systematic methods to handle uncertainty in models and forecasts. Vehicle connectivity creates more accurate and broad environment sensing and more comprehensive energy cost estimations.

    - The effect of eco-routing (and routing algorithms in general) at the network level (rather than at the vehicle level only) is not well understood yet.

Outline

- Overview of Connected and Automated Electric Vehicles

- Electric Vehicle Energy Consumption Modeling

- Energy Efficiency Driving Technologies

  – Eco-Driving

  – Eco-Routing

- **Automatic Charging Decision Making for Connected and Automated Electric Vehicles**

Integrated Energy Management of Connected Automated Electric Vehicles

- **Overview of integrated energy management for CAEVs**

Energy Consumption
Eco-driving/Eco-routing

Energy Management of Automated EVs

Energy Recharging
Charging Decision Making
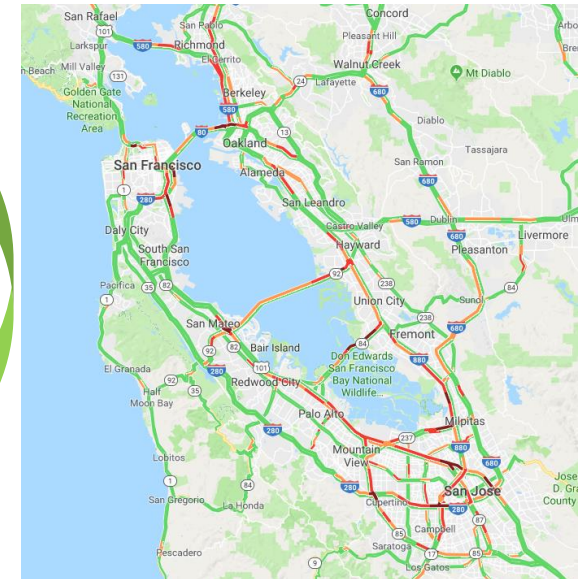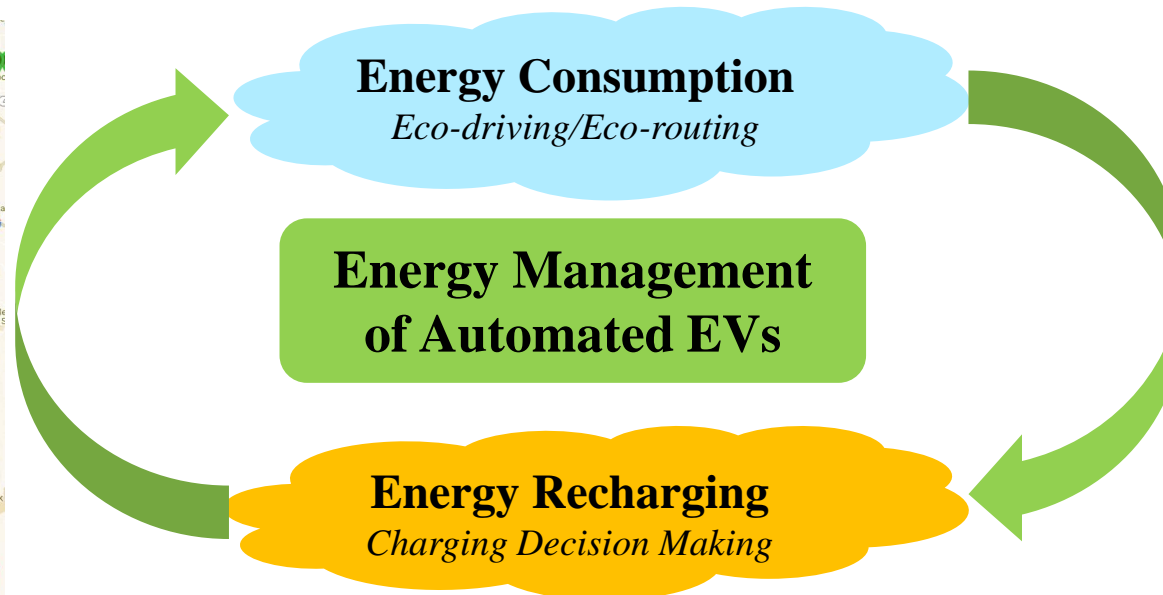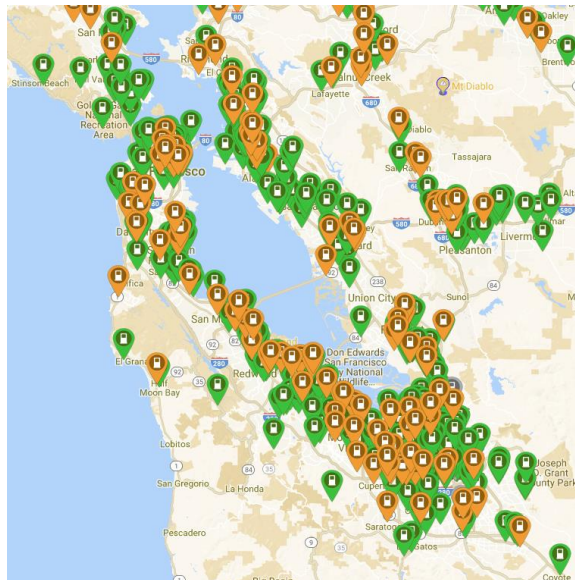
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Opportunities from Automated Electric Vehicles

Connected Automated EVs

Automatic Charging Station
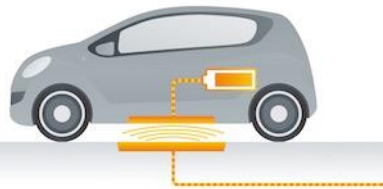
Wireless Charging

Photo Source:
http://www.ipwatchdog.com/2015/06/18/wireless-induction-charging-is-coming-to-electric-vehicles/id=58756/

Photo Source:
https://patents.google.com/patent/US9527403
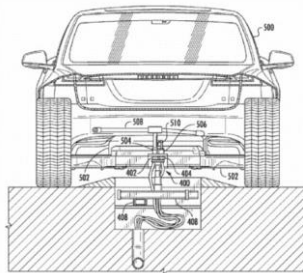
Automatic Charging Decision Making

- An automatic decision making process is necessary for charging of automated electric vehicles

- Remove the challenge of co-locating charging infrastructure with driver destinations

- Utilize real-time charging station status information

Connected Charging Station Network
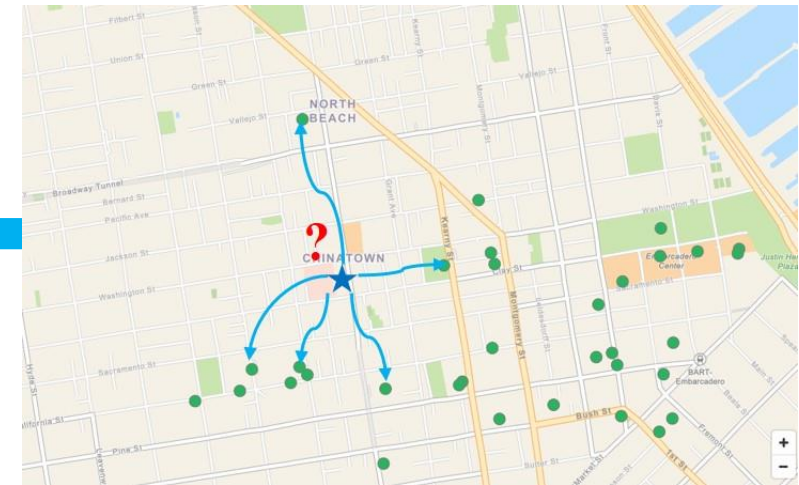
Benefits

- Ensure sufficient battery energy to meet travel needs

- Minimize the energy/time/money cost of charging actions

- Facilitate the charging control and vehicle/grid integration

A Framework for Automatic Charging Decision Making

Travel/Itinerary Information
- Visited locations
- Staying time
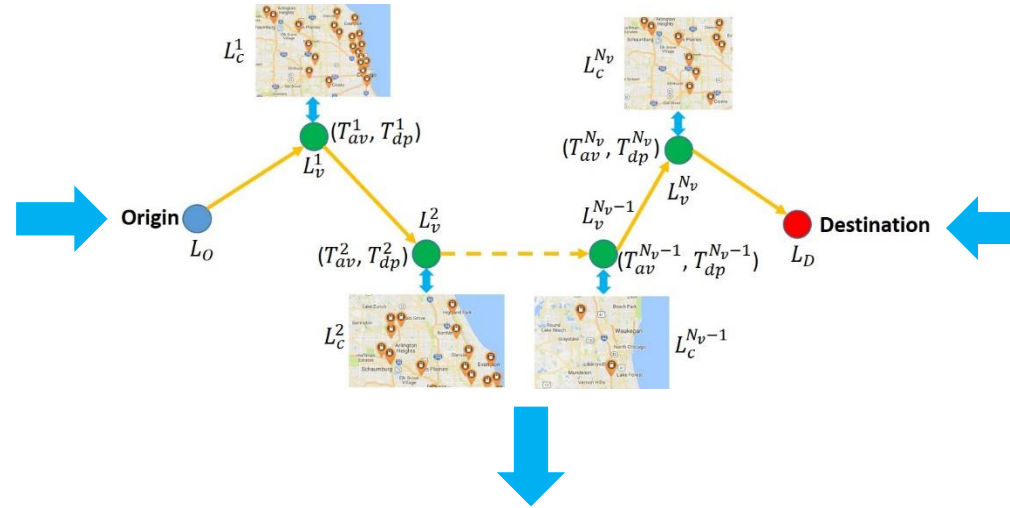
Nearby Charging Station Network
- Location
- Availability
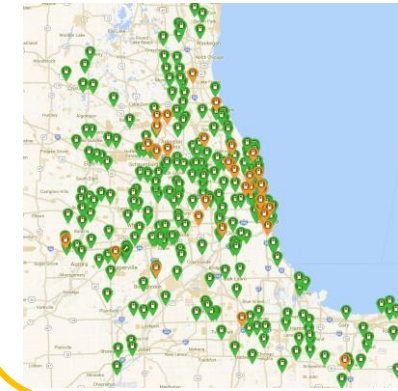
EV Energy Consumption Model
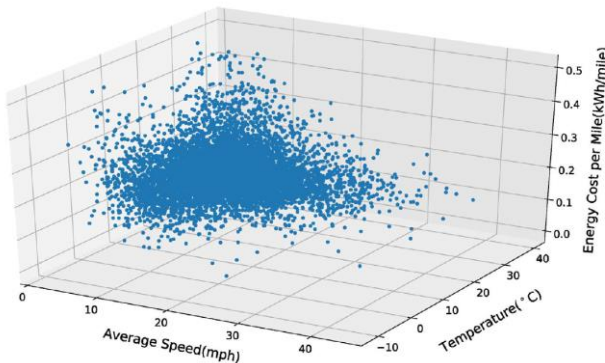
Multi-Stage Dynamic Programming

$$\min_{a[1],\ldots,a[N_v]} \quad f(s[0], a[0], 0) + \sum_{k=1}^{N_v} f(s[k], a[k], k)$$

$$\text{s.t.} \quad s[0] = S_0$$

$$s[k-1] = s[k] - \sum_{i=1}^{N_c^k} E_c^i[k]x^i[k] + E_{tc}^{(k-1,k)} + 2\sum_{i=1}^{N_c^k} E_{cc}^i[k]x^i[k]$$

$$P_d[k] \le s[k] \le C_p$$

$$0 \le E_c^i[k] \le E_{upr}^i[k]$$

$$x^i[k] = 0 \quad \text{or} \quad 1, \quad \text{and} \quad \sum_{i=1}^{N_c^k} x^i[k] \le 1$$

$$k = 1, \ldots, N_v$$

Optimized Charging Strategies
- Charging location
- Charging energy amount
- Charging time interval

Dynamic Programming for Charging Decision Making

- **Multi-Stage Charging Decision Making Modeling**

Deterministic (Average) Modeling

$$\min_{a[1],\ldots,a[N_v]} \quad f(s[0],a[0],0) + \sum_{k=1}^{N_v} f(s[k],a[k],k)$$

$$\text{s.t.} \quad s[0] = S_0$$

$$s[k-1] = s[k] - \sum_{i=1}^{N_c^k} E_c^i[k]x^i[k] + E_{tc}^{(k-1,k)} + 2\sum_{i=1}^{N_c^k} E_{cc}^i[k]x^i[k]$$

$$P_d[k] \le s[k] \le C_p$$

$$0 \le E_c^i[k] \le E_{upr}^i[k]$$

$$x^i[k] = 0 \text{ or } 1, \text{ and } \sum_{i=1}^{N_c^k} x^i[k] \le 1$$

$$k = 1,\ldots,N_v$$

Robust Modeling

$$\min_{a[1],\ldots,a[N_v]} \quad \max_{\substack{E_{tc}^{(k,k+1)} \in [E_{lw}^k, E_{up}^k] \\ E_{cc}^i[k] \in [E_{lw}^i[k], E_{up}^i[k]]}} f(s[0],a[0],0) + \sum_{k=1}^{N_v} f(s[k],a[k],k)$$

$$\text{s.t.} \quad s[0] = S_0$$

$$s[k-1] = s[k] - E_c[k] + E_{tc}^{(k-1\to k)} + 2\sum_{i=1}^{N_c^k} E_{cc}^i[k]x^i[k]$$

$$P_d[k] \le s[k] \le C_p$$

$$0 \le E_c^i[k] \le E_{upr}^i[k]$$

$$E_c[k] = \sum_{i=1}^{N_c^k} E_c^i[k]x^i[k]$$

$$x^i[k] = 0 \text{ or } 1, \text{ and } \sum_{i=1}^{N_c^k} x^i[k] \le 1$$

$$k = 1,\ldots,N_v$$

Energy Cost Prediction

- One-step prediction

$$P_d[k] = E_{tc}^{(k,k+1)}$$

- Two-step prediction

$$P_d[k] = E_{tc}^{(k\to k+1)} + E_{tc}^{(k+1,k+2)}$$

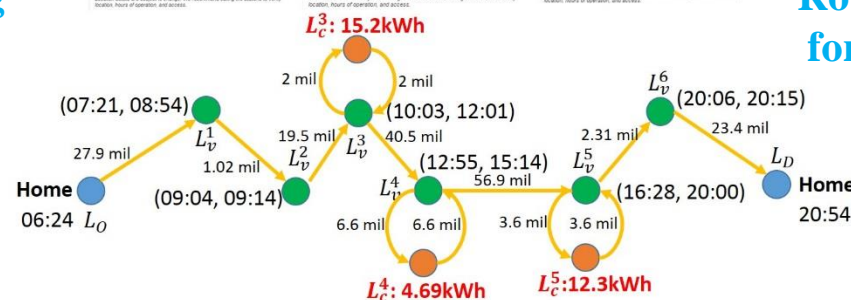## Objective Function: (Energy, Economy, etc.)

$$f(s[k],a[k],k) = \sum_{i=1}^{N_c[k]} E_c^i[k]P_r^i[k]x^i[k] + \lambda \sum_{i=1}^{N_c[k]} E_{cc}^i[k]x^i[k]$$

Simulation Studies

A daily trip in Chicago
1->2->3->4->5->6->7->1
Location: Arrival Time-Departure Time
1: 20:54 - 06:24
2: 07:21 - 08:54
3: 09:04 - 09:14
4: 10:03 - 12:01
5: 12:55 - 15:14
6: 16:28 - 20:00
7: 20:06 - 20:15

Level 2 Charging Stations

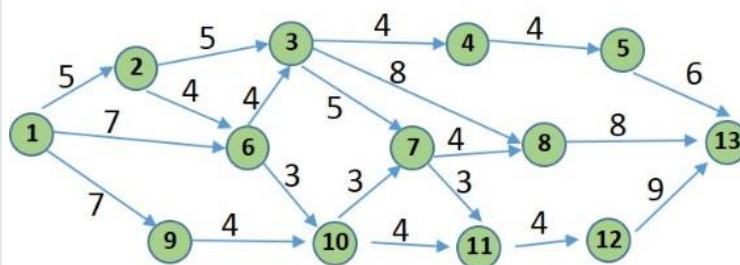DC Fast Charging Stations
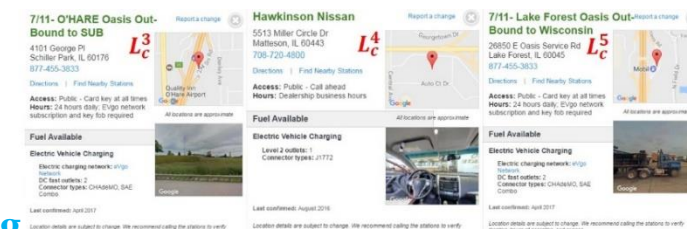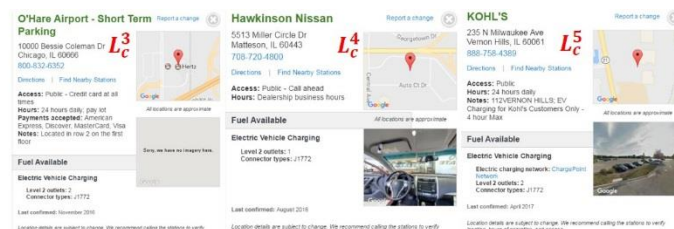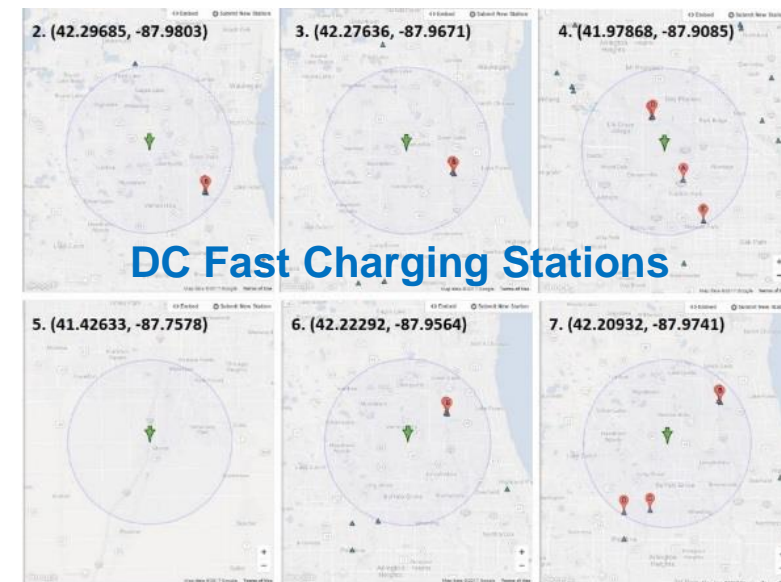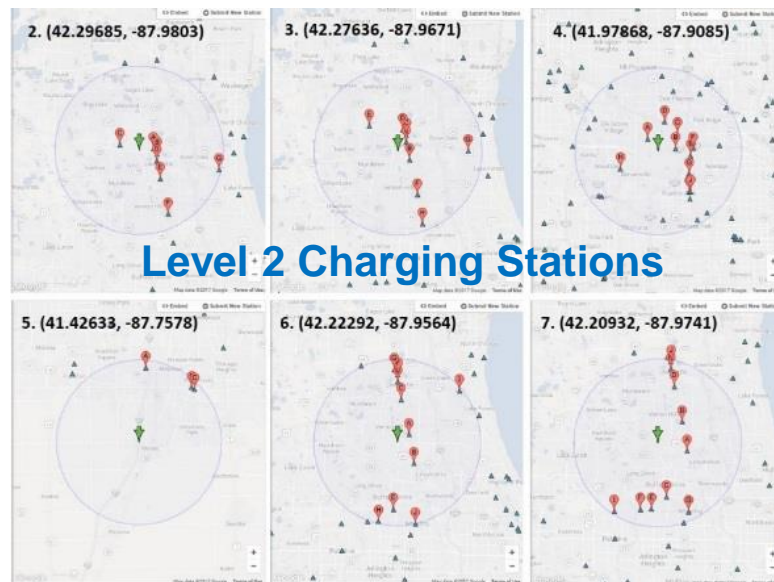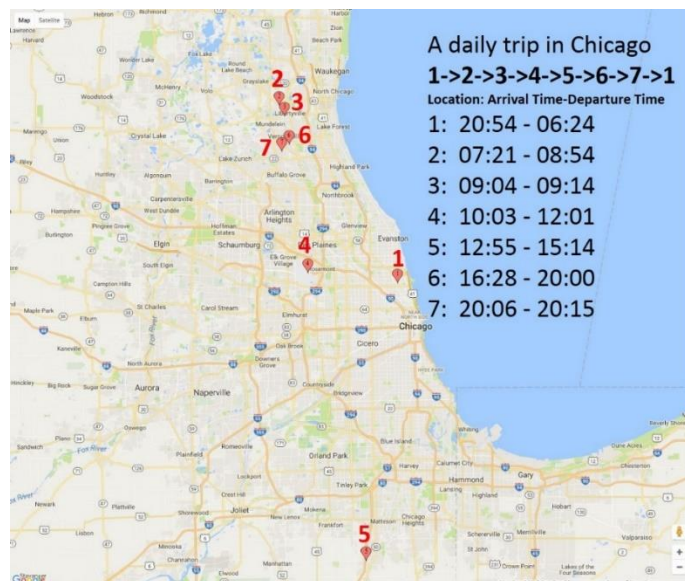
Average Decision Making
for Charging Strategies

Robust Decision Making
for Charging Strategies
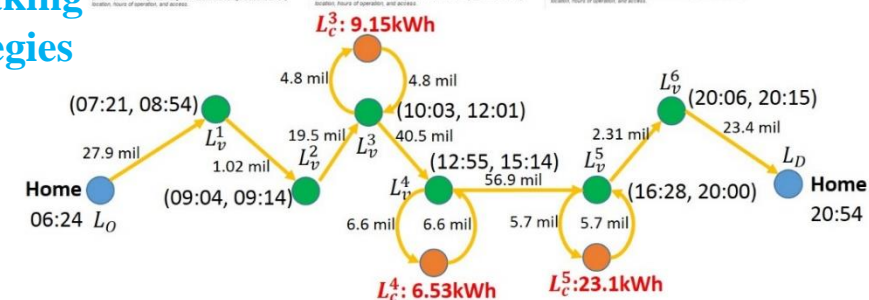
Eco-Routing and Charging Decision Making for Automated EV Fleet

- **Optimization Model for Simultaneously Routing and Charging Decision Making**

$$\min_{x_{ij}} \sum_{i=1}^{N} \sum_{j=1}^{N} E_{ij} x_{ij}$$

$$\text{s.t.} \quad \sum_{j \in O(i)} x_{ij} - \sum_{j \in I(i)} x_{ji} = b_i$$

$$b_o = 1, \ b_d = -1, \ b_i = 0 \ when \ i \in \mathcal{N}/\{o, d\}$$

$$E_j = \sum_{i \in I(j)} (E_i + t_c^i P_i - E_{ij}) x_{ij} \quad j \in \mathcal{N}/\{o\}$$

$$t_o + \sum_{i=1}^{N} \sum_{j=1}^{N} t_{ij} x_{ij} + \sum_{i=1}^{N} t_c^i \le t_d$$

$$0 \le E_i \le C_p$$

$$0 \le t_c^i \le M P_i$$

$$x_{ij} = 0 \ \text{or} \ 1$$

$$E_d \ge E_{req}$$

Case 1: no charging station and energy requirement
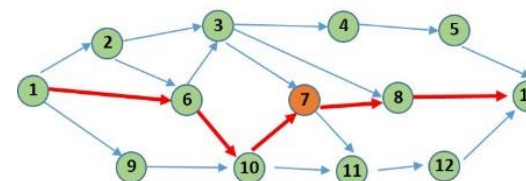Case 2, 3, 4: DC fast charging station and energy requirement with E1=10kWh and E13=20kWh
Case 5, 6: Level 2 charging station in Node 3 and DC fast charging station in Node 10 with energy requirement and different travel time requirements
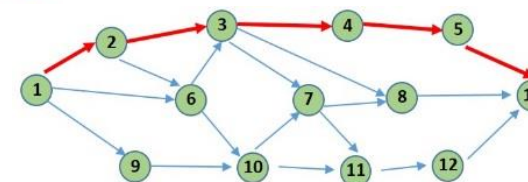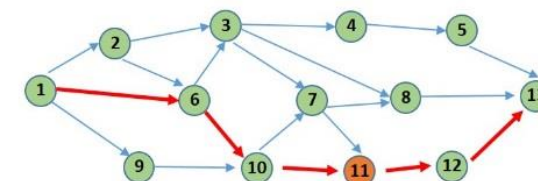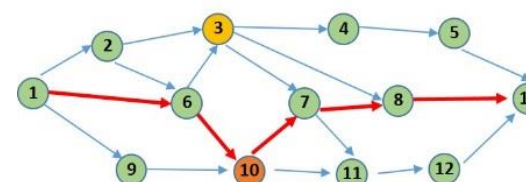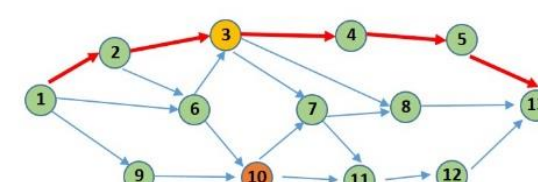

Case 1
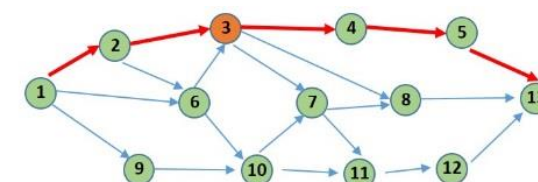
Case 2

Case 3

Case 4

Case 5

Case 6

Objective

- Select the route with minimum energy cost and simultaneously charge vehicles automatically to satisfy the battery energy requirement in an autonomous EV fleet

Eco-Routing and Charging Decision Making for Automated EV Fleet

- **Valuable Findings**
  - Energy management for an autonomous EV fleet is sensitive to the realistic environmental conditions, e.g. ambient temperature.
  - Individually routing and charging decision making of CAEVs can cause problematic coincident charging demand pattern without coordination.
  - It is important and necessary to design and manage autonomous fleet system cooperatively between automatic decision making in CAEV and infrastructure system planning.
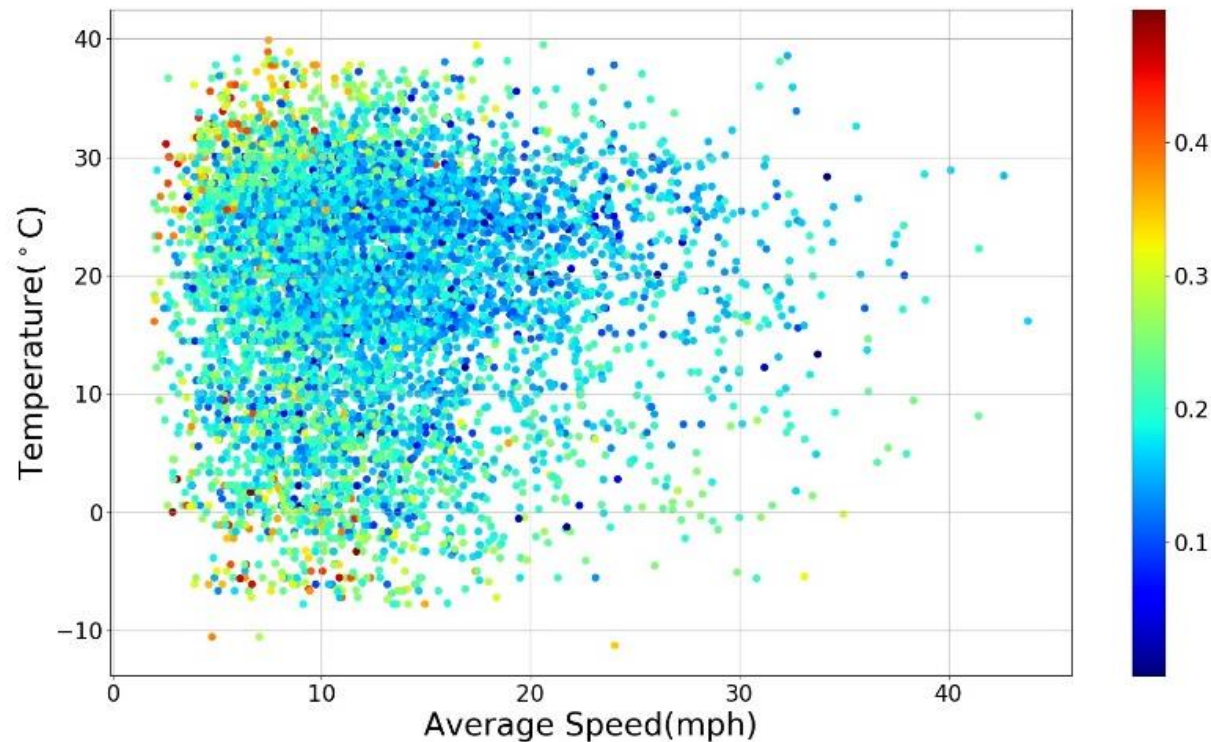
Month	Temperature(℃) (Low, High)	Month	Temperature(℃) (Low, High)
January	(-3.1, 3.8)	February	(-1.9, 5.5)
March	(1.9, 9.9)	April	(6.9, 15.7)
May	(12.6, 21.5)	June	(17.7, 26.3)
July	(21, 29.3)	August	(20.3, 28.4)
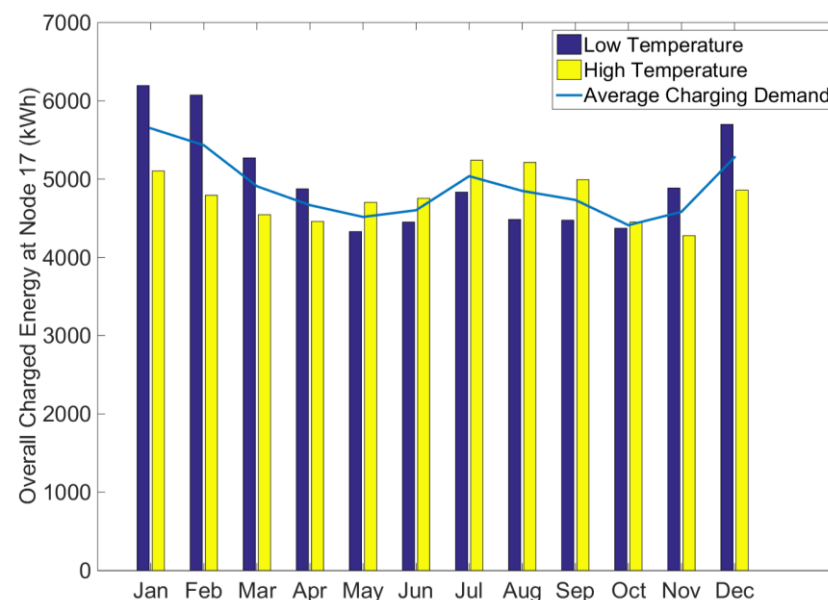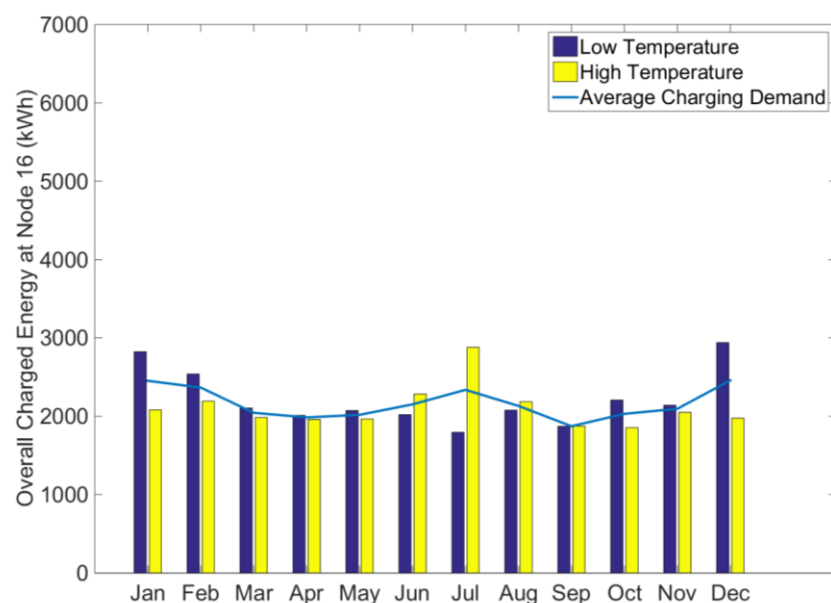
> A simulated fleet with 100 CAEVs
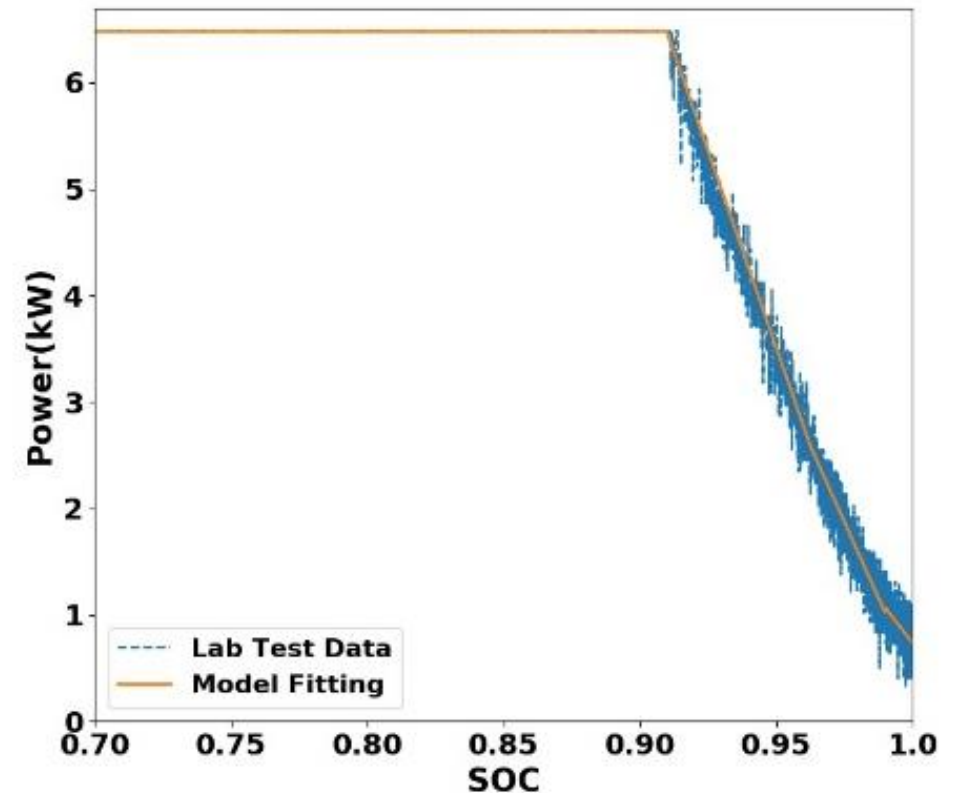> Each CAEV in fleet performs 100 O-D trips

Vehicle Level Challenges for Integrated Energy Management of CAEVs

- **Energy Consumption Dynamics**

- **Charging Power Dynamics**

Energy cost per mile of Nissan Leaf Taxi with regard to average vehicle speed and ambient temperature in New York City

Realistic *charging power* **data for a 2015 Nissan Leaf**
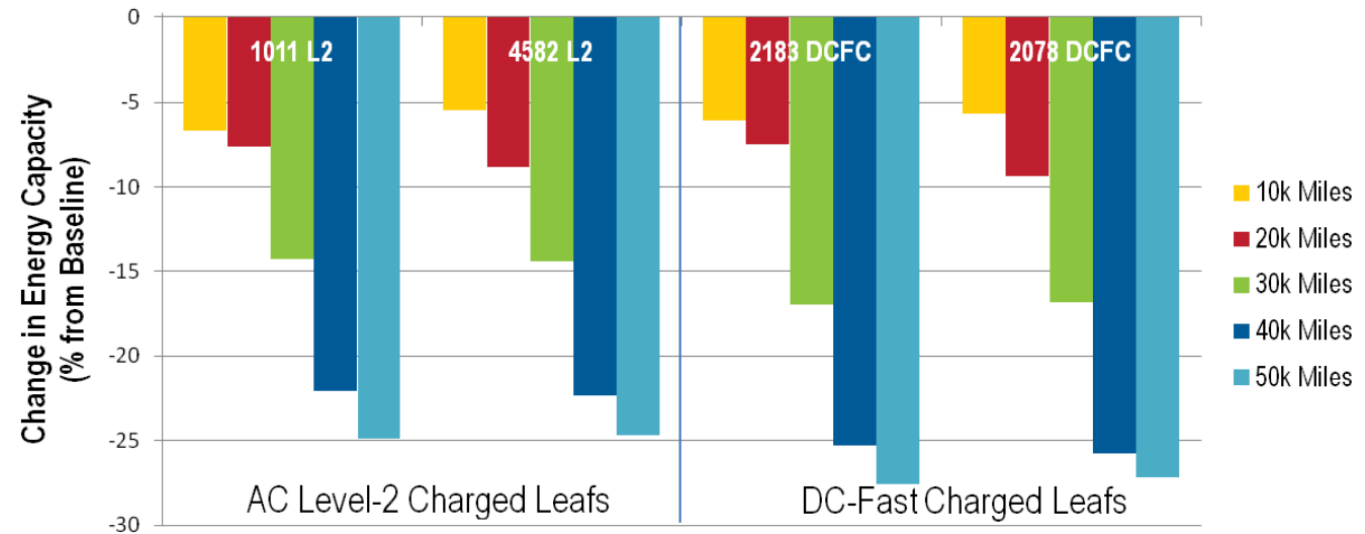
Vehicle Level Challenges for Integrated Energy Management of CAEVs

- **Impact of High Power Charging to Battery Life**

A rendering of a *350kW XFC charging station* **by Electrek.**
Source: https://www.energy.gov/eere/vehicles/downloads/enabling-extreme-fast-charging-technology-gap-assessment
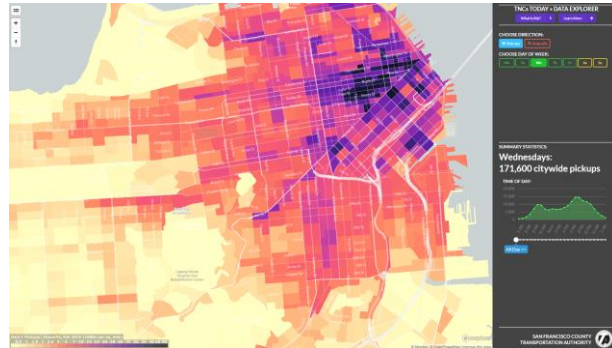

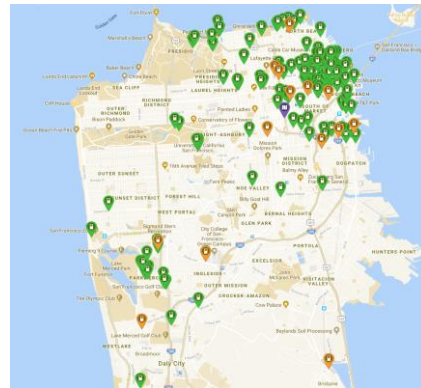*Percent change in energy capacity* **from baseline**
Source: https://www.energy.gov/sites/prod/files/2015/01/f19/dcfc_study_fs_50k.pdf

System Level Challenges for Integrated Energy Management of CAEVs

Spatiotemporal travel demand

Source: http://tncstoday.sfcta.org/

Centralized vs Decentralized
- Communication cost
- Computing cost

Systematic Energy Management for Personal/Shared Automated EV Fleet

Eco-Routing/Eco-Driving

Co-Optimization

Automatic Charging Decision Making

Charging Infrastructure Network
- Different charging power levels
- Dynamic utilization pattern

Charging Infrastructure Network

Autonomous Electric Vehicle Fleet

Passenger Requests
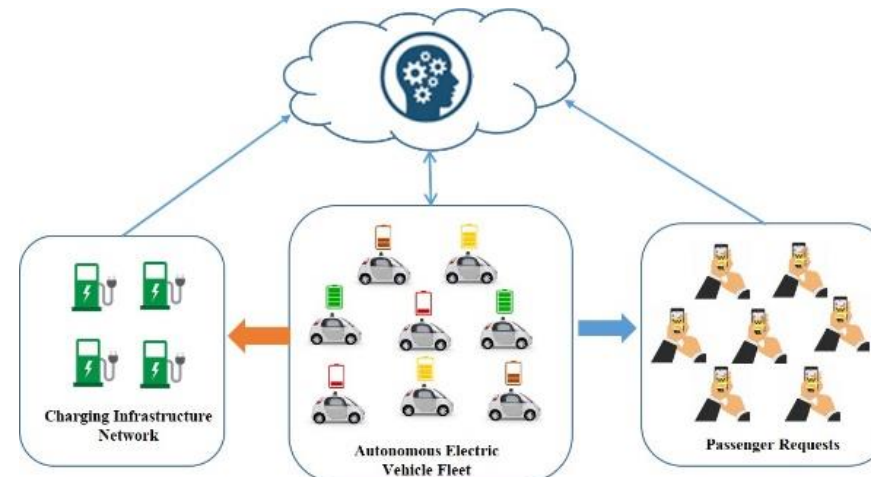
Summary

- An introduction to connected and automated electric vehicles has been provided. Future intelligent transportation and energy management applications are summarized and illustrated.

- Modeling technologies of electric vehicle energy consumption are introduced, i.e. physical based and data driven methods. Some opportunities from vehicle automation and communication are identified.

- Two types of trip level energy efficiency driving technologies, i.e. eco-driving and eco-routing, are introduced. Specific research questions and scenarios are illustrated, and their potential methods and challenges are summarized.

- Automatic charging decision making for CAEVs are introduced to investigate the possibility of integrated energy management for future CAEV transportation systems. Challenges from both vehicle and transportation system levels are identified for promising future research.