Electrified Vehicle Energy Management: Solutions and Opportunities

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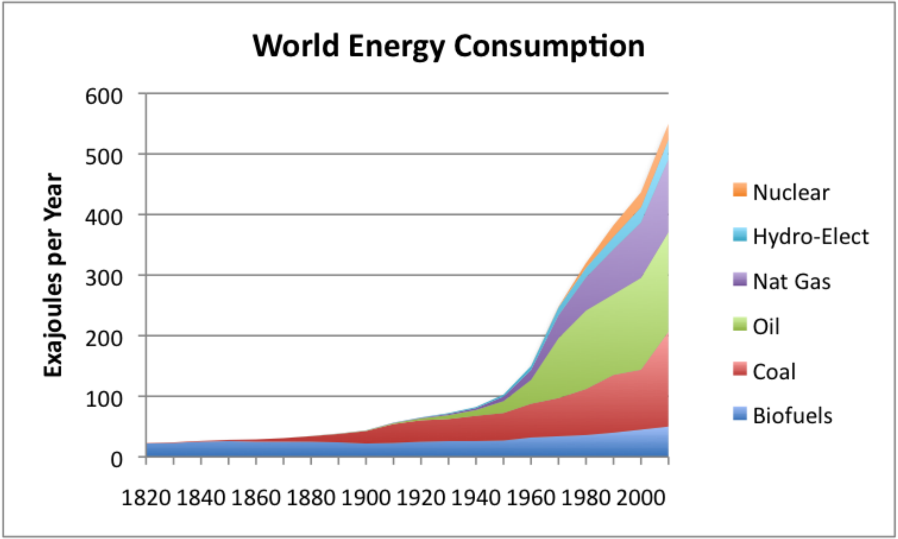
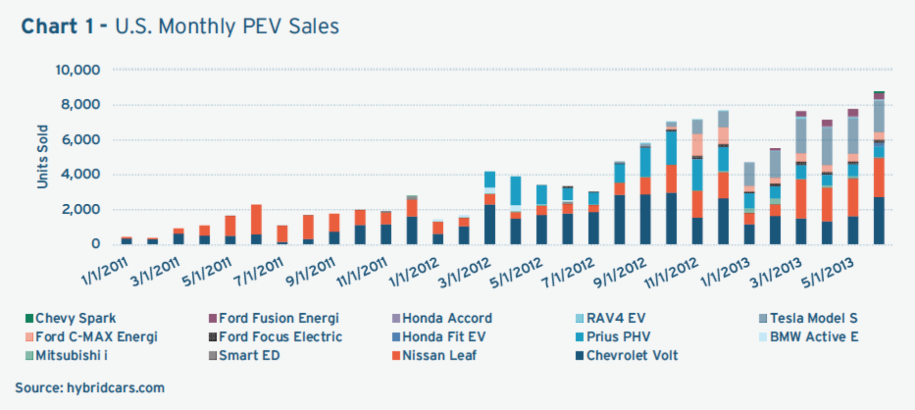
i4Energy | CITIRS

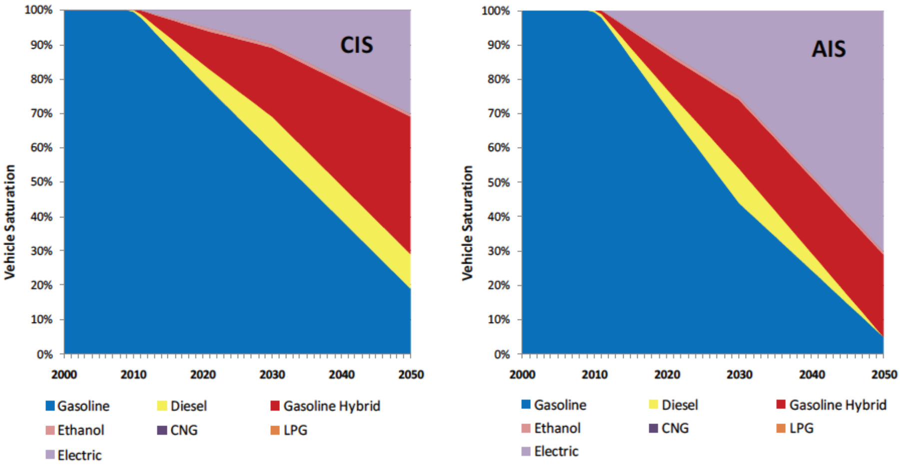


Source: Vaclav Smil Estimates from Energy Transitions



500,000 electric drive vehicles sold in U.S. (2012)

53,000 PEVs sold in U.S. (2012)



HEVs, EVs projected to dominate transportation market in China by 2050

Zhou, Nan, David Fridley, Michael McNeil, Nina Zheng, Jing Ke, and Mark Levine. "China's Energy and Carbon Emissions Outlook to 2050," Lawrence Berkeley National Laboratory Tech Report LBNL-4472E (2011)

Energy Crisis Solutions

Electrified Transportation	Smart Grids
(e.g., batteries, energy management)	(e.g., demand response)

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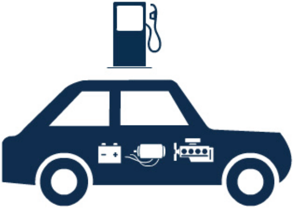
Electric Drive Vehicle Basics

Hybrid Electric Vehicles (HEV)



- Internal combustion (IC) engine is primary energy source
- Battery serves as buffer

Ex: Toyota Prius

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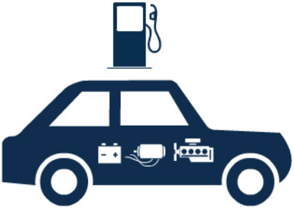

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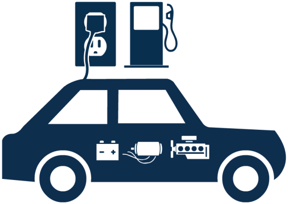
Plug-in Hybrid Electric Vehicles (PHEV)

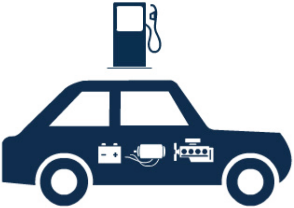


- IC engine & battery are depletable stores
- Fuel at station, charge with plug

Ex: Chevy Volt

Electric Drive Vehicle Basics

Hybrid Electric Vehicles (HEV)



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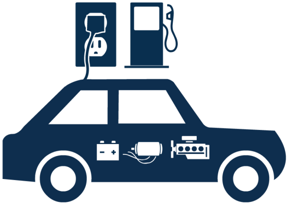

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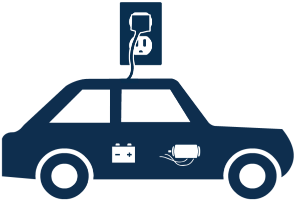
All-Electric Vehicle (EV)



- Battery only, no engine
- Requires charging to "re-fuel"

Ex: Nissan Leaf, Tesla Model S

Outline

1. Electrochemical-based Battery SOC/SOH Estimation
   - N. Chaturvedi (Bosch RTC) and M. Krstic (UCSD)
2. PHEV Energy Management for Battery Health
   - H. Fathy (Penn State), D. Callaway (UCB), and J. Stein (Michigan)
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4. Coming Soon...

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The Battery Problem

Needs: Cheap, high energy/power, fast charge, long life

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Some Motivating Facts

EV Batts	1000 USD / kWh (2010)* 485 USD / kWh (2012)* 125 USD / kWh for parity to IC engine Only 50-80% of available capacity is used Range anxiety inhibits adoption Lifetime risks caused by fast charging

*Source: MIT Technology Review, "The Electric Car is Here to Stay." (2013)

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Two Solutions

Design better batteries (materials science & chemistry)	Make current batteries better (estimation and control)

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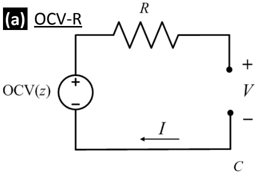
Battery Models

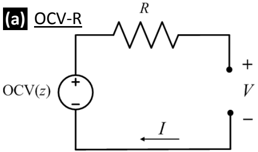
Equivalent Circuit Model



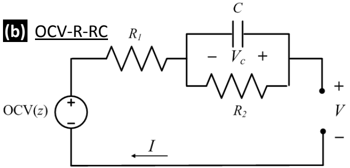
Battery Models

Equivalent Circuit Model

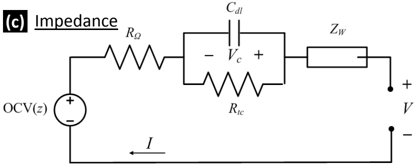
(a) OCV-R



(b) OCV-R-RC



(c) Impedance



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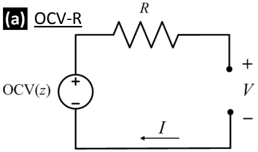

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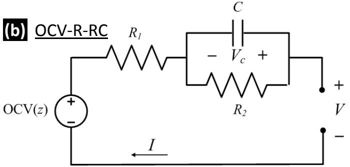

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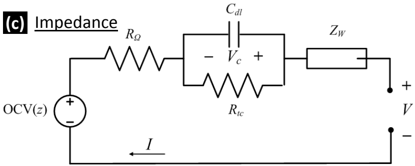
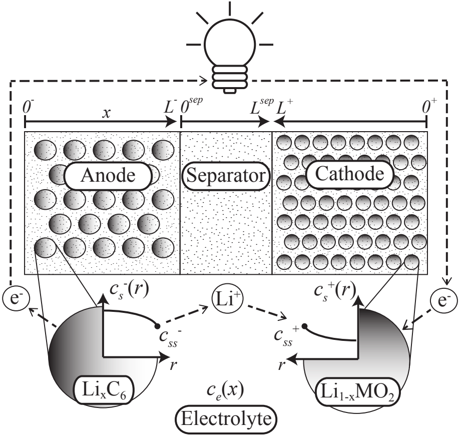
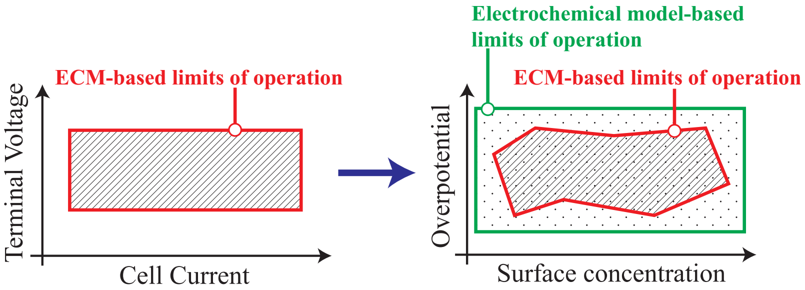


Electrochemical Model



Operate Batteries at their Physical Limits



Electrochemical Model Equations

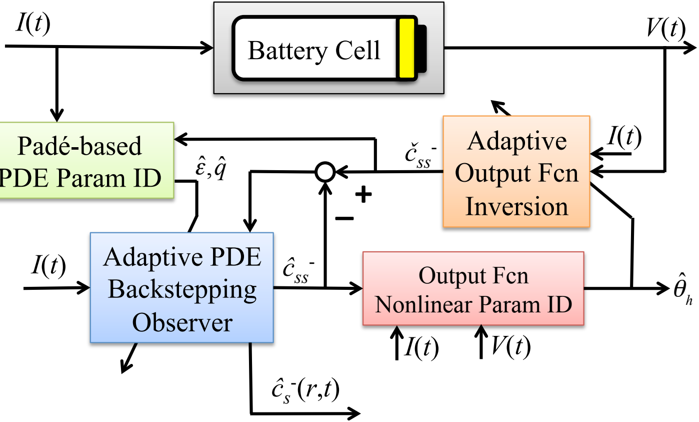
well, some of them

Description	Equation
Solid phase Li concentration	$\frac{\partial c_s^\pm}{\partial t}(x,r,t) = \frac{1}{r^2}\frac{\partial}{\partial r}\left[D_s^\pm r^2 \frac{\partial c_s^\pm}{\partial r}(x,r,t)\right]$
Electrolyte Li concentration	$\varepsilon_e \frac{\partial c_e}{\partial t}(x,t) = \frac{\partial}{\partial x}\left[\varepsilon_e D_e \frac{\partial c_e}{\partial x}(x,t) + \frac{1-t_c^0}{F} i_e^\pm(x,t)\right]$
Solid potential	$\frac{\partial \phi_s^\pm}{\partial x}(x,t) = \frac{i_e^\pm(x,t) - I(t)}{\sigma^\pm}$
Electrolyte potential	$\frac{\partial \phi_e}{\partial x}(x,t) = -\frac{i_e^\pm(x,t)}{\kappa} + \frac{2RT}{F}(1-t_c^0)\left(1 + \frac{d \ln f_{c/a}}{d \ln c_e}(x,t)\right)\frac{\partial \ln c_e}{\partial x}(x,t)$
Electrolyte ionic current	$\frac{\partial i_e^\pm}{\partial x}(x,t) = a_s F j_n^\pm(x,t)$
Molar flux btw phases	$j_n^\pm(x,t) = \frac{1}{F} i_0^\pm(x,t)\left[e^{\frac{\alpha_a F}{RT}\eta^\pm(x,t)} - e^{-\frac{\alpha_c F}{RT}\eta^\pm(x,t)}\right]$
Temperature	$\rho c_P \frac{dT}{dt}(t) = h\left[T^0(t) - T(t)\right] + I(t)V(t) - \int_{0^-}^{0^+} a_s F j_n(x,t)\Delta T(x,t)dx$

Animation of Li Ion Evolution

Adaptive Observer

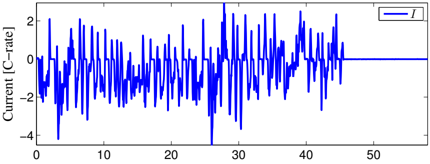
Combined State & Parameter Estimation



S. J. Moura, N. A. Chaturvedi, M. Krstic, "Adaptive PDE Observer for Battery SOC/SOH Estimation via an Electrochemical Model," *ASME Journal of Dynamic Systems, Measurement, and Control*, 2013.

Results

UDDS Drive Cycle Input



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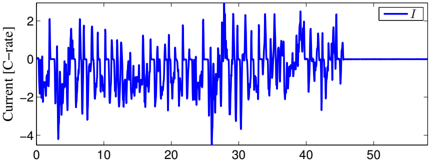

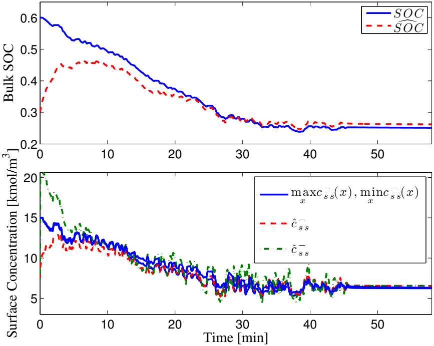

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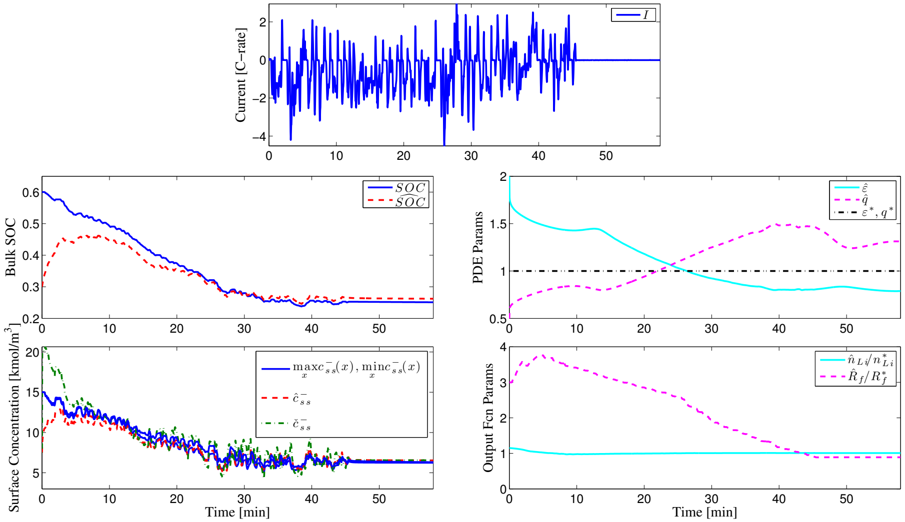
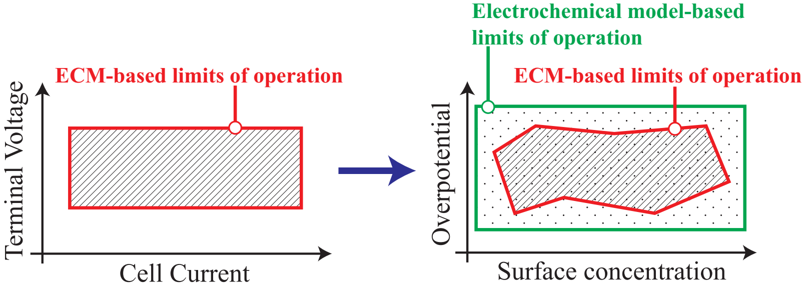


Operate Batteries at their Physical Limits

Problem Statement

Given accurate state estimates, govern the electric current such that safe operating constraints are satisfied.

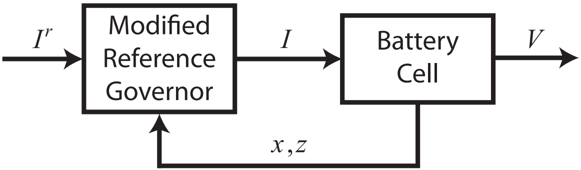


Constraints

Variable	Definition	Constraint
$I(t)$	Current	Power electronics limits
$c_s^{\pm}(x,r,t)$	Li concentration in solid	Saturation/depletion
$\frac{\partial c_s^{\pm}}{\partial r}(x,r,t)$	Li concentration gradient	Diffusion-induced stress
$c_e(x,t)$	Li concentration in electrolyte	Saturation/depletion
$T(t)$	Temperature	High/low temps accel. aging
$\eta_s(x,t)$	Side-rxn overpotential	Li plating, dendrite formation

Each variable, y, must satisfy $y_{\min} \leq y \leq y_{\max}$.

The Algorithm: Modified Reference Governor (MRG)



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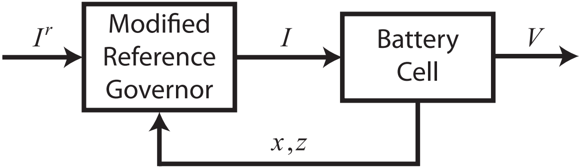

MRG Equations

$$I[k+1] = \beta^*[k] I^r[k], \qquad \beta^* \in [0,1],$$

$$\beta^*[k] = \max \left\{ \beta \in [0,1] : (x(t), z(t)) \in \mathcal{O} \right\}$$

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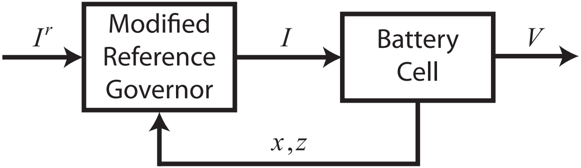

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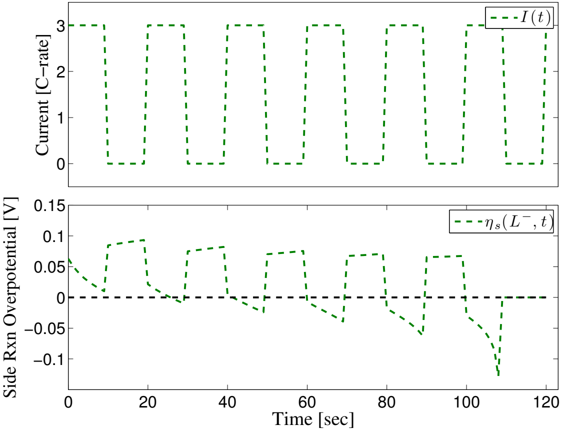
Def'n: Admissible Set $\mathcal{O}$

$$\mathcal{O} = \left\{(x(t), z(t)) : y(\tau) \in \mathcal{Y}, \forall \tau \in [t, t+T_s]\right\}$$
$$\begin{aligned} \dot{x}(t) &= f(x(t), z(t), \beta I^r) \\ 0 &= g(x(t), z(t), \beta I^r) \\ y(t) &= C_1 x(t) + C_2 z(t) + D \cdot \beta I^r + E \end{aligned}$$

Constrained Control of EChem States



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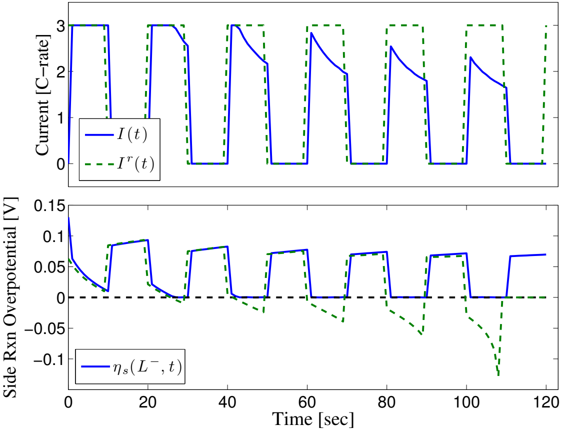
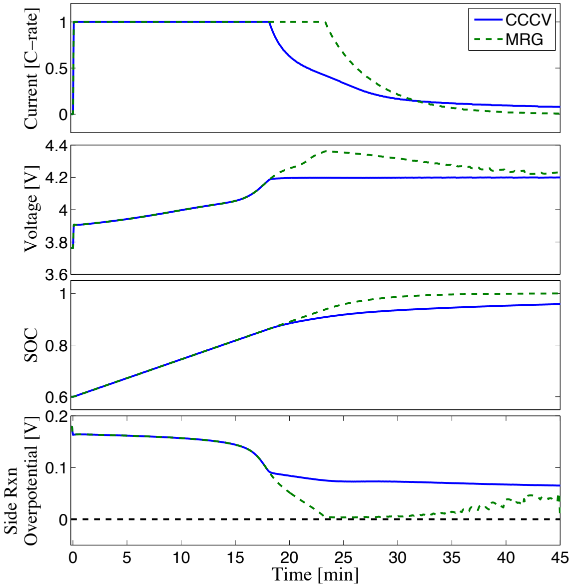


Application to Charging



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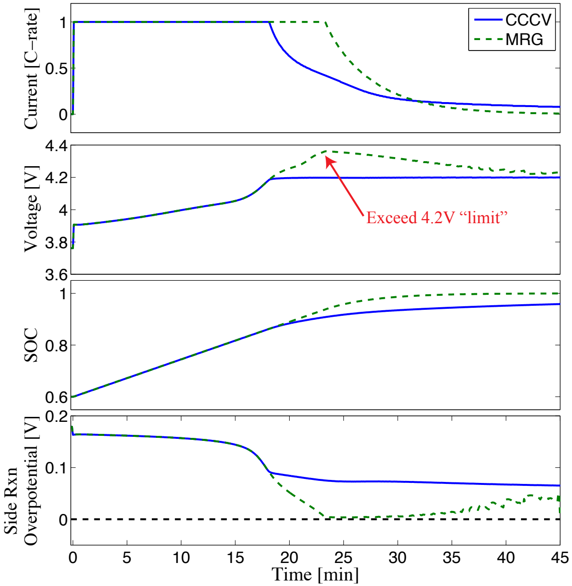

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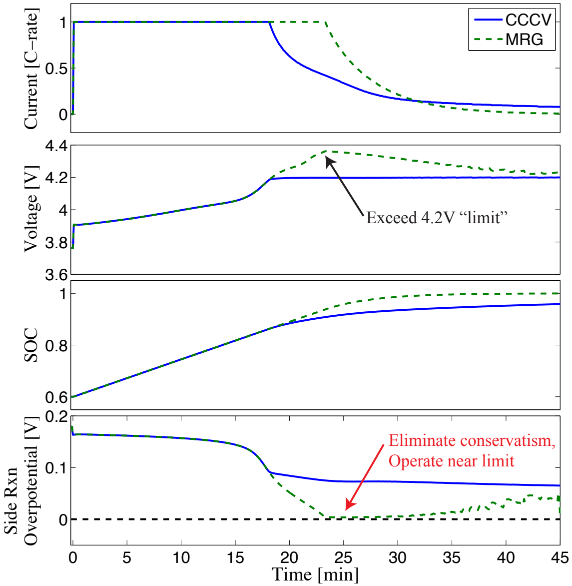

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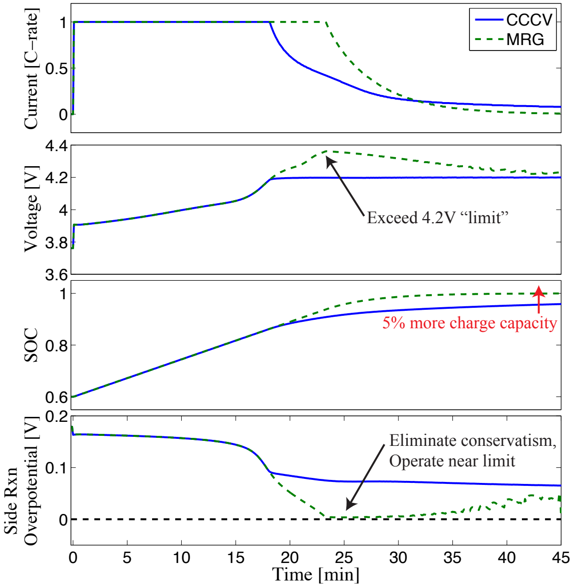

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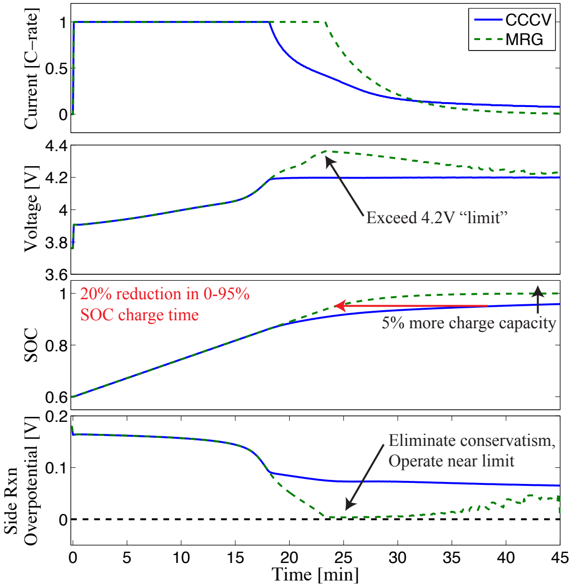
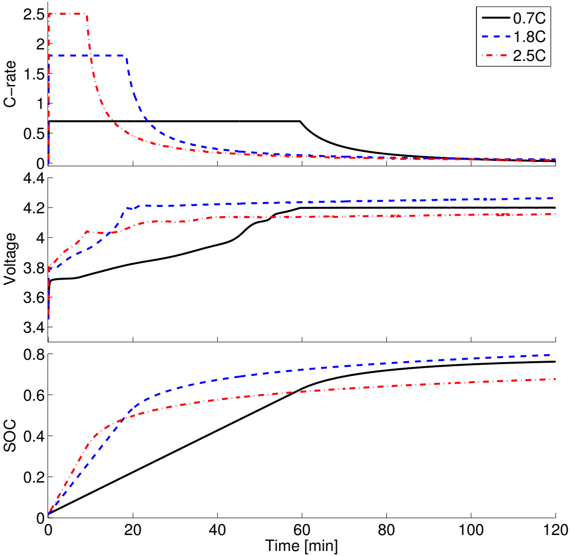


Fast Charging



Fast charge your smartphone/EV while getting coffee

Table: Simulated fast charge times for various C-rates

Charge range	**0.7C** | Traditional	**1.8C** | ECC	**2.5C** | ECC
0-10%	7.92 min	3.17 min	2.33 min
0-20%	17.83 min	7.00 min	5.08 min
0-50%	47.33 min	18.42 min	20.50 min

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4. Coming Soon...

Problem Statement

Design a supervisory control algorithm for plug-in hybrid electric vehicles (PHEVs) that splits engine and battery power in some optimal sense.

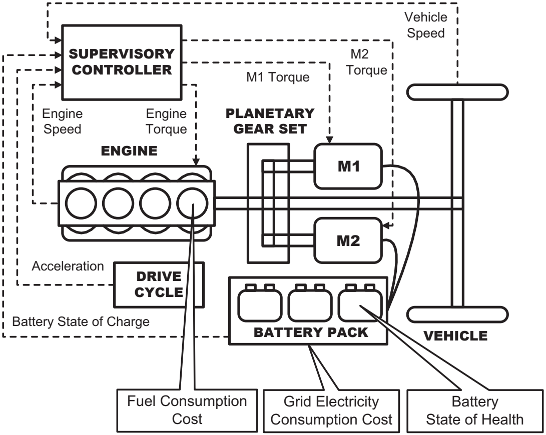
J. Voelcker, "Plugging Away in a Prius," *IEEE Spectrum*, vol. 45, pp. 30-48, 2008.

Power-Split PHEV Model

Ex: Toyota Prius, Ford Escape Hybrid

- Control Inputs
  - Engine Torque
  - M1 Torque

- State Variables
  - Engine speed
  - Vehicle speed
  - Battery SOC
  - Vehicle acceleration (Markov Chain)



Control Optimization: Minimize energy consumption cost AND battery aging

Stochastic Dynamic Programming

Cost Functional:

$$J^g = \lim_{N \to \infty} \mathrm{E} \left[\sum_{k=0}^{N} c(x_k, u_k) \right]$$

Constraints:

$$\begin{aligned} x_{k+1} &= f(x_k, u_k, w_k) \\ x &\in X \\ u &\in U(x) \end{aligned}$$

Objective:

$$g^* = \arg\min_{g \in G} J^g$$

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Cost per time step: Convex sum of energy cost and battery health

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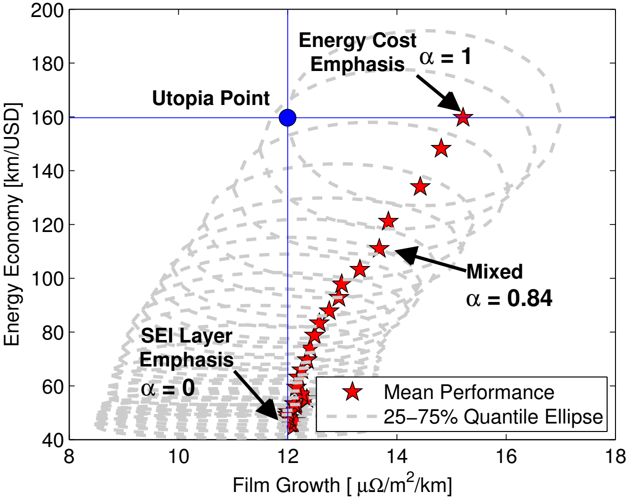
Energy: $c_E(x_k, u_k) = \beta W_{fuel} + \dfrac{-V_{oc} Q_{batt} \dot{SOC}}{\eta_{EVSE}}$

Health: $c_H(x_k, u_k) = \dot{\delta}_{film}(I, SOC)$

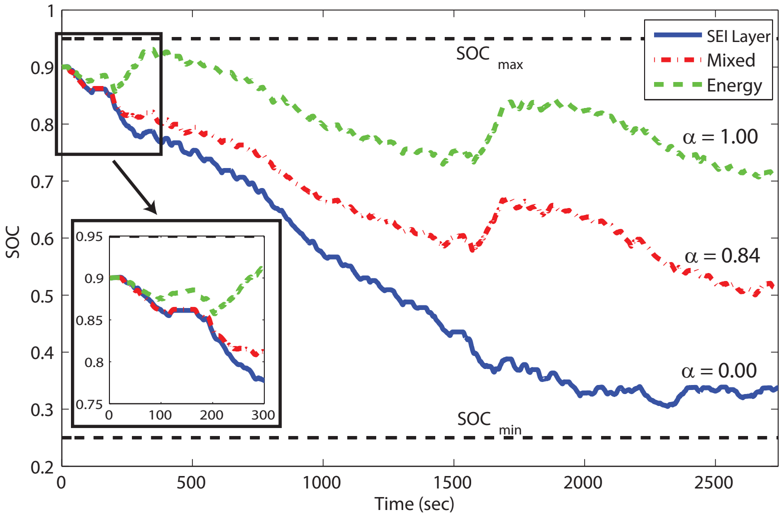
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth



SOC Trajectories

Anode-side SEI Layer Growth | UDDSx2



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Fact: Given perfect drive cycle info, we can achieve provably optimal economy

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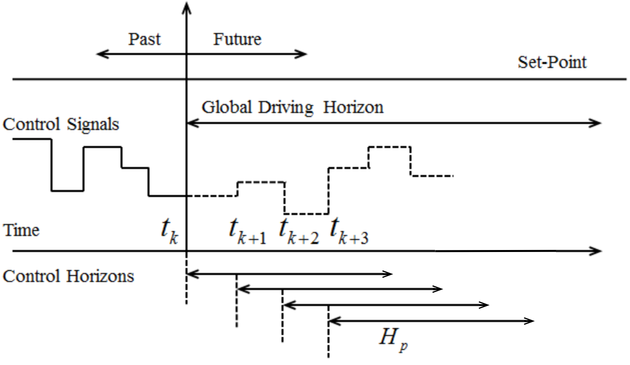
Consider Model Predictive Control (MPC)

By forecasting velocity over a 'short' receding horizon, we can optimize economy



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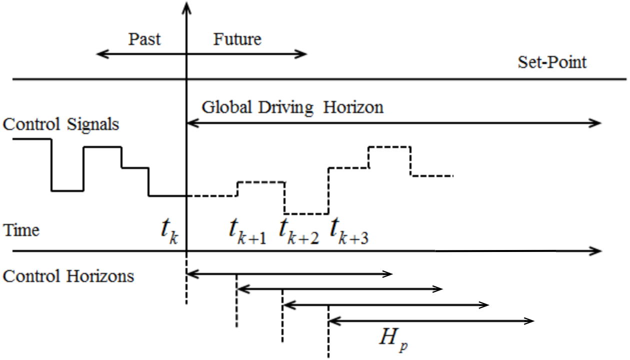
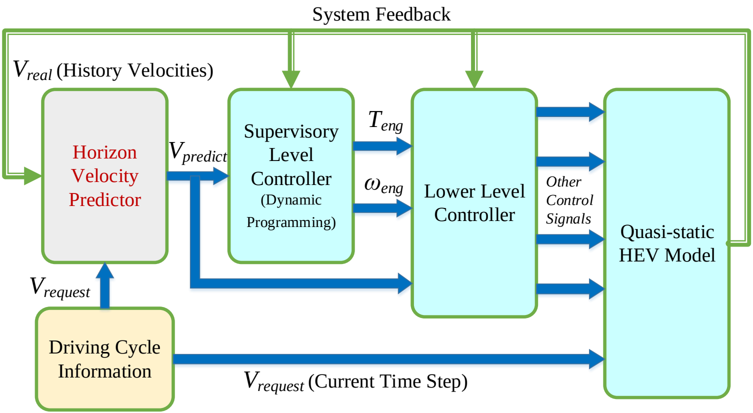


Punchline: Better velocity forecasts produce lower fuel consumption and emissions

MPC Energy Management w/ Velocity Prediction



Candidate Velocity Predictors

1. Generalized exponentially varying
2. Markov chain models
3. Artificial Neural Networks

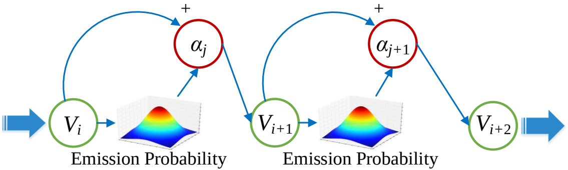
Candidate Velocity Predictors

1. Generalized exponentially varying
   - Generalization of a heuristic in the MPC energy management literature
2. Markov chain models
3. Artificial Neural Networks

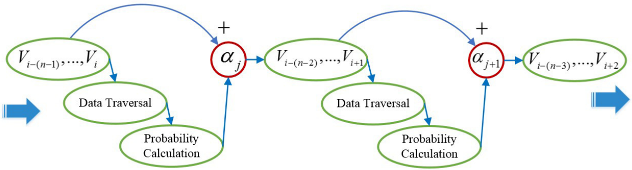
$$V_{k+n} = (1+\varepsilon)^n V_k, \text{ for } n = 1, 2, ..., H_p$$

Candidate Velocity Predictors

1. Generalized exponentially varying
2. Markov chain models
    - One-stage
    - Multi-stage
3. Artificial Neural Networks



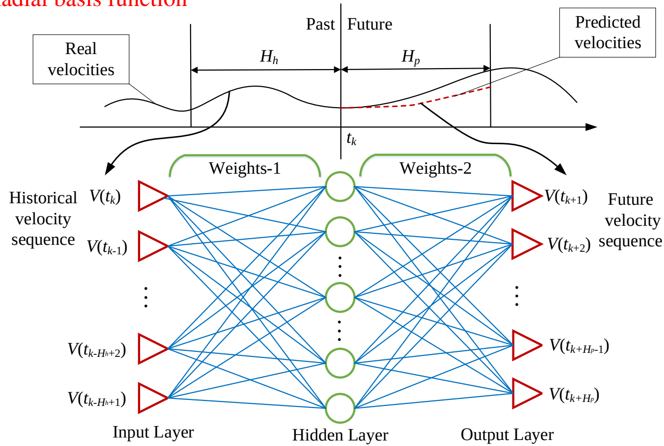
One-stage



Multi-stage

Candidate Velocity Predictors

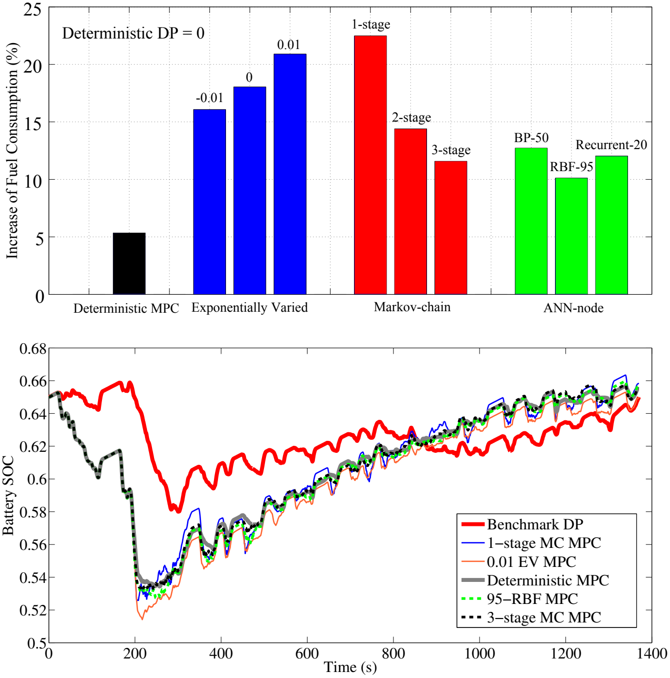
1. Generalized exponentially varying
2. Markov chain models
3. Artificial Neural Networks
   - Back propagation
   - Layer recurrent
   - Radial basis function

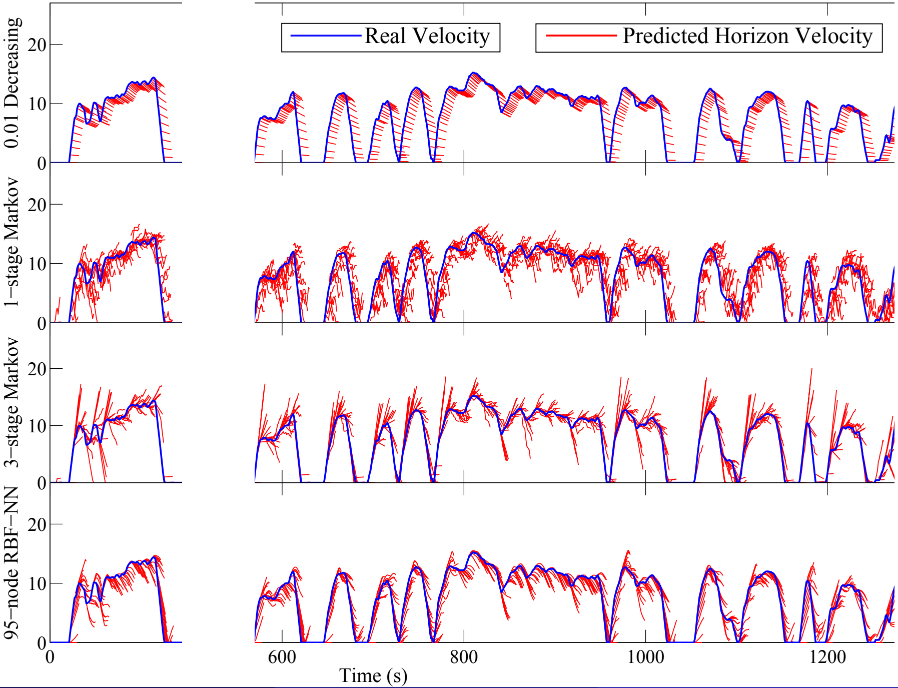


Comparison on UDDS

Methods	Vel. RMSE	Fuel (g)	Sim. time (sec)
Deterministic DP	–	**335**	–
Deterministic MPC	–	**353**	–
-0.01 EV	2.08	389	0.032
1-stage MC	2.33	410	1.647
3-stage MC	1.62	374	2.919
RBF-95 ANN	1.57	369	0.208

DP = Dynamic programming; MPC = Model predictive control;
EV = Exponentially Varying; MC = Markov-chain;
ANN = Artificial neural network

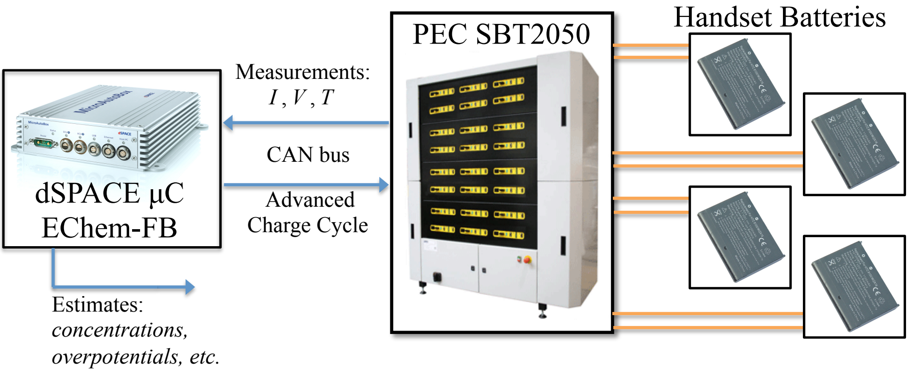

Deterministic DP = 0
Increase of Fuel Consumption (%)
25
20
15
10
5
0
-0.01
0
0.01
1-stage
2-stage
3-stage
BP-50
RBF-95
Recurrent-20
Deterministic MPC
Exponentially Varied
Markov-chain
ANN-node
Battery SOC
0.68
0.66
0.64
0.62
0.6
0.58
0.56
0.54
0.52
0.5
0
200
400
600
800
1000
1200
1400
Time (s)
Benchmark DP
1−stage MC MPC
0.01 EV MPC
Deterministic MPC
95−RBF MPC
3−stage MC MPC


Real Velocity
Predicted Horizon Velocity
0.01 Decreasing
1−stage Markov
3−stage Markov
95−node RBF−NN
20
10
0
0
600
800
1000
1200
Time (s)

Outline

1. Electrochemical-based Battery SOC/SOH Estimation
   - N. Chaturvedi (Bosch RTC) and M. Krstic (UCSD)
2. PHEV Energy Management for Battery Health
   - H. Fathy (Penn State), D. Callaway (UCB), and J. Stein (Michigan)
3. Velocity Forecasting for Predictive Energy Management
   - C. Sun (UCB/BIT), X. Hu (Chalmers), F. Sun (BIT)
4. Coming Soon...

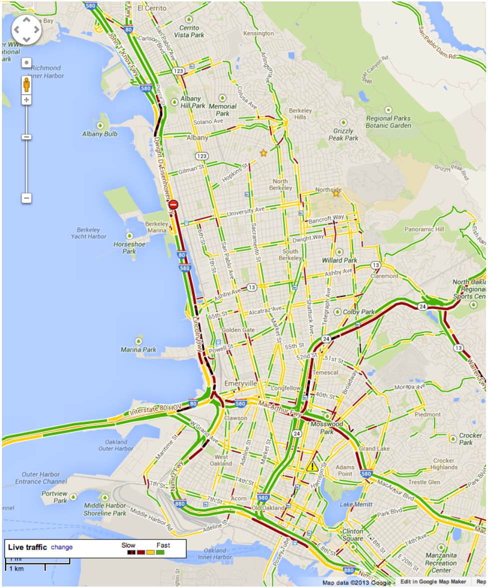
Fast Charging



Motivation in Mobile Communication:

6.7B subscription accounts, 5.2B handsets in use, 1.7B sold worldwide in 2012

Optimize PHEV Energy Management w/ Real-time Traffic Data



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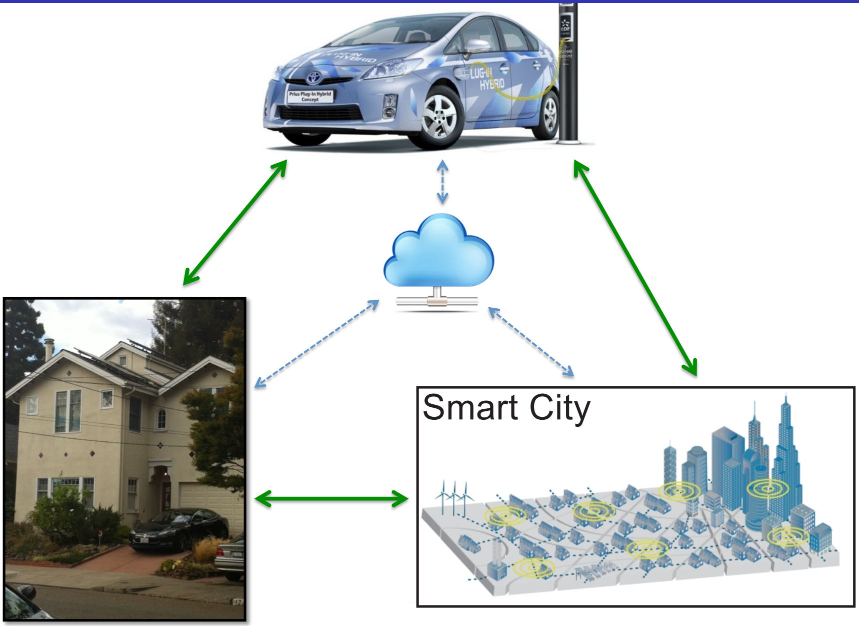
Vehicle - Home / City / Grid Integration



CE 186

DESIGN OF CYBER-PHYSICAL SYSTEMS

Spring 2014: Mon & Wed 2-4

Topics Include:

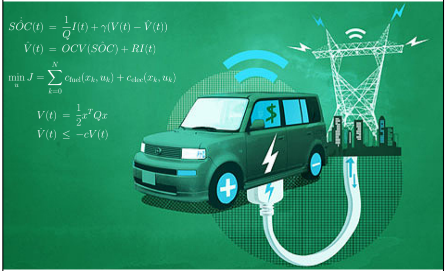
- Energy Management and Power Systems
- Vehicle-to-Grid and Battery Models
- Internet-based Systems
- Data Collection and Analysis

CE 290:002

ENERGY SYSTEMS & CONTROL

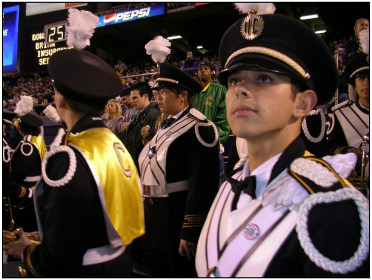
Spring 2014: MWF 10-11

Prof. Scott Moura



Topics Include:

- Energy Storage & Renewables
- Electrified Transportation
- State estimation
- Optimal control



Go Bears!

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