Hybrid Electric Vehicle Energy Management: Solutions and Opportunities

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Workshop for New Energy Vehicle
Dynamic System and Control Technology
Beijing, China
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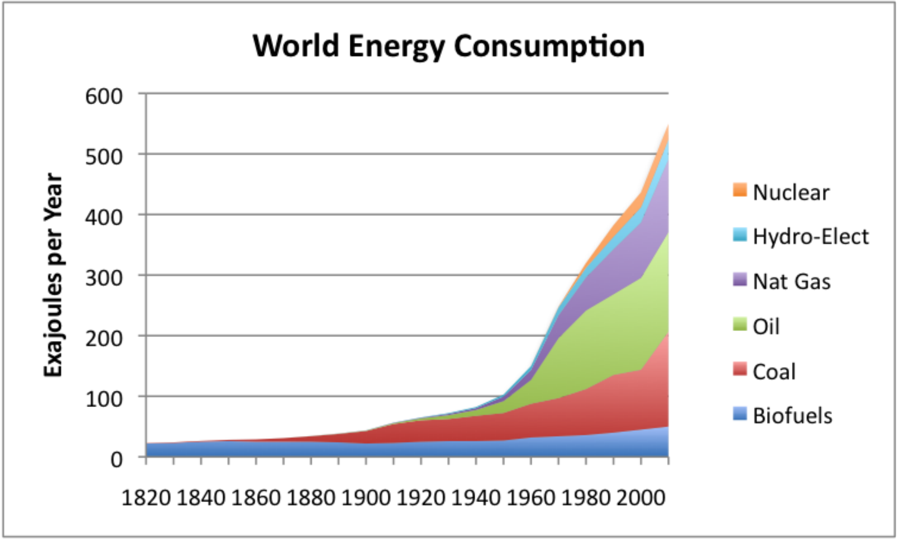
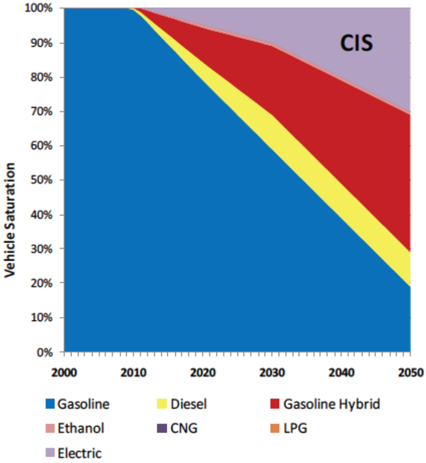
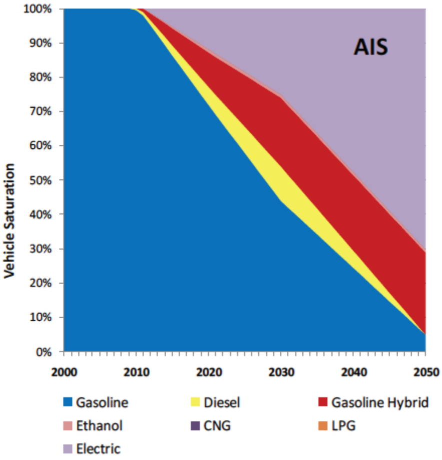


Source: Vaclav Smil Estimates from Energy Transitions





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

Smart Grids	Electrified Transportation
(e.g., demand response)	(e.g., hybrid vehicles)

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Outline

1. Electrochemical-based Battery SOC/SOH Estimation
2. PHEV Energy Management for Battery Health
3. Velocity Forecasting for Predictive Energy Management
4. Opportunities

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The Battery Problem

Needs: Cheap, high energy, high power, long life

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Some Motivating Facts

EV Batts	800 USD / kWh now (2010) 125 USD / kWh for parity to IC engine Only 75% of available capacity is used Range anxiety inhibits adoption Lifetime risks caused by fast charging

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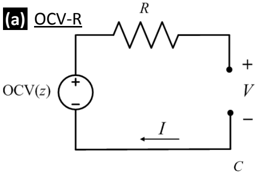
Two Solutions

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

Battery Models

Equivalent Circuit Model

(a) OCV-R



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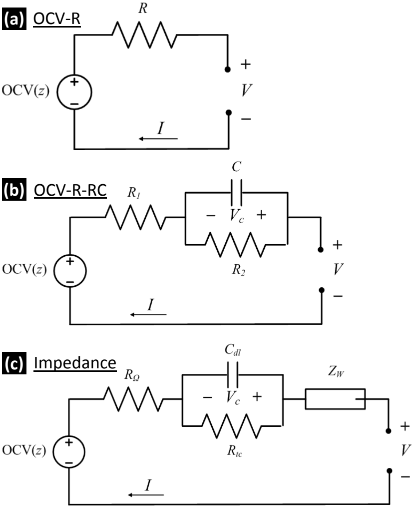

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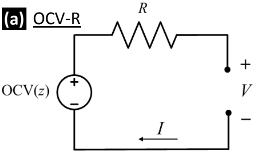
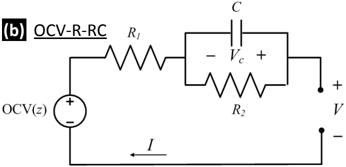
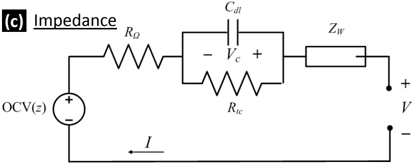


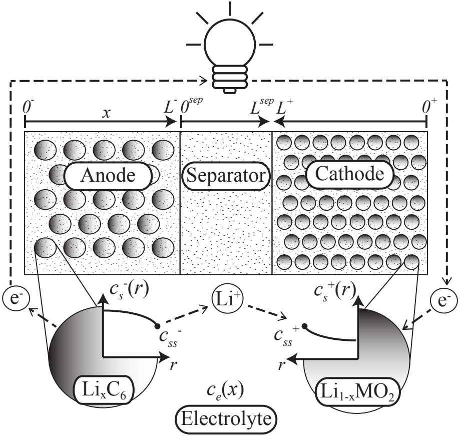
(b) OCV-R-RC



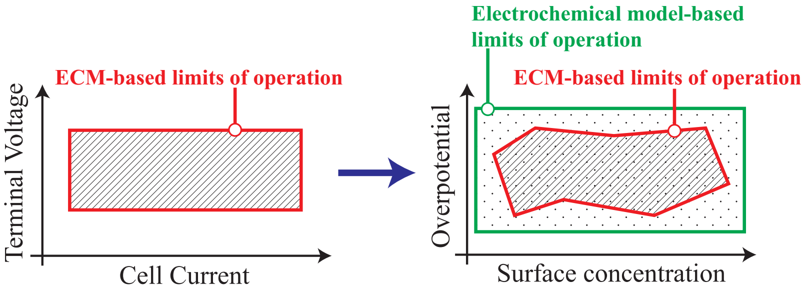
(c) Impedance



Electrochemical Model



Operate Batteries at their Physical Limits



Electrochemical Model Equations

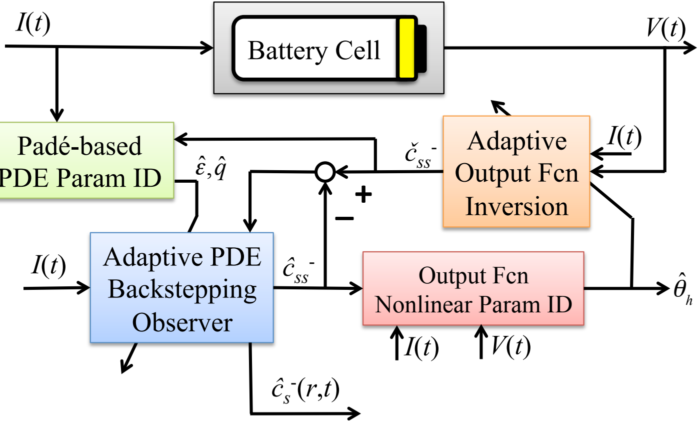
well, some of them

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

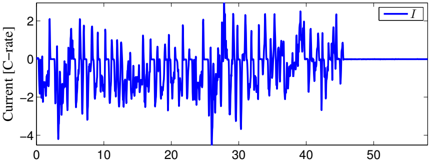
Combined State & Parameter Estimation



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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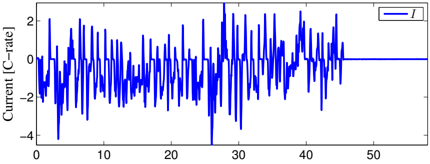

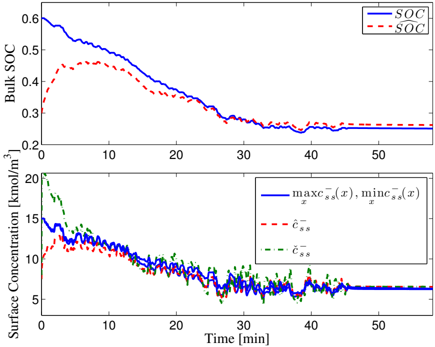

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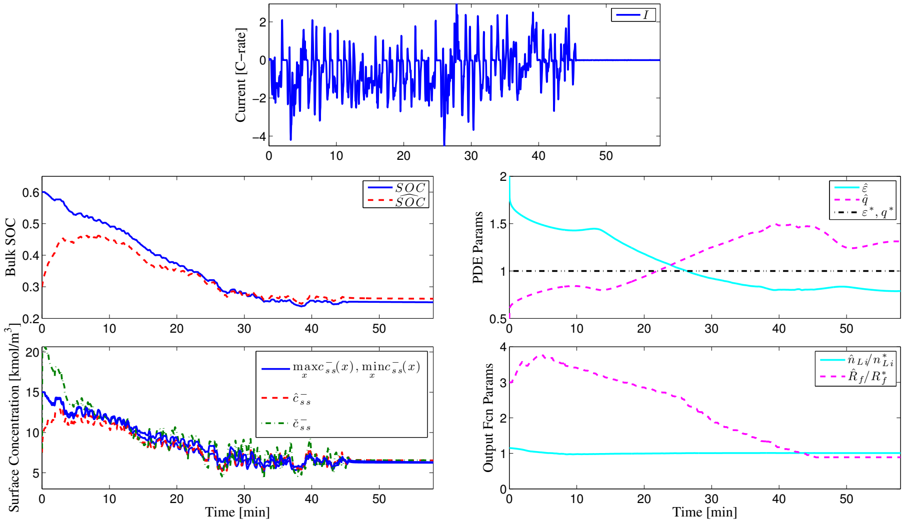
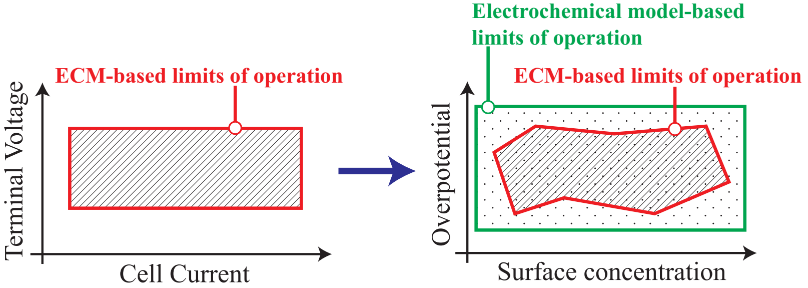


Operate Batteries at their Physical Limits

Problem Statement

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

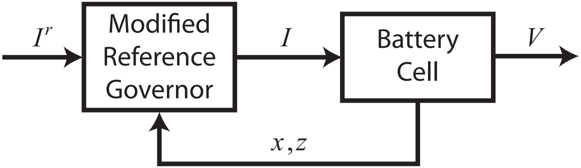


Constraints

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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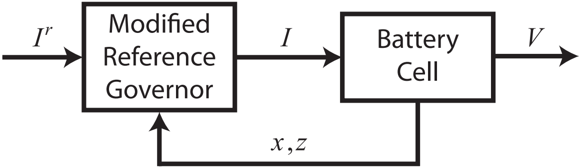

MRG Equations

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

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

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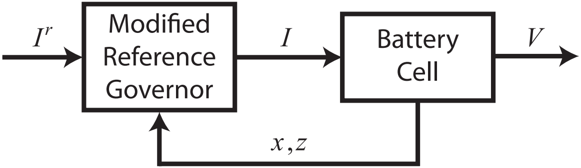

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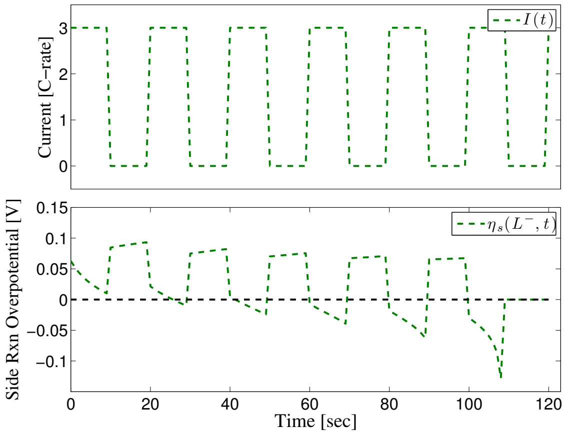
Def'n: Admissible Set $\mathcal{O}$

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

Constrained Control of EChem States



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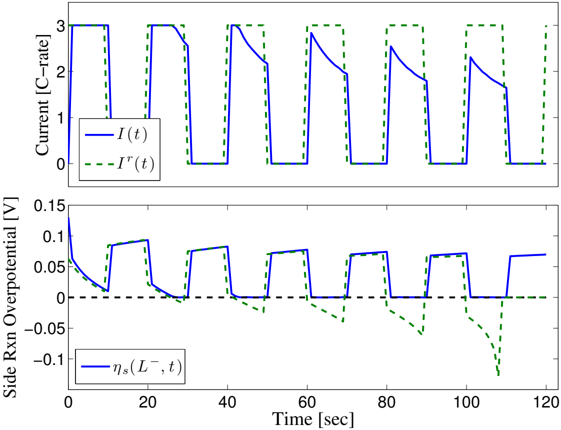
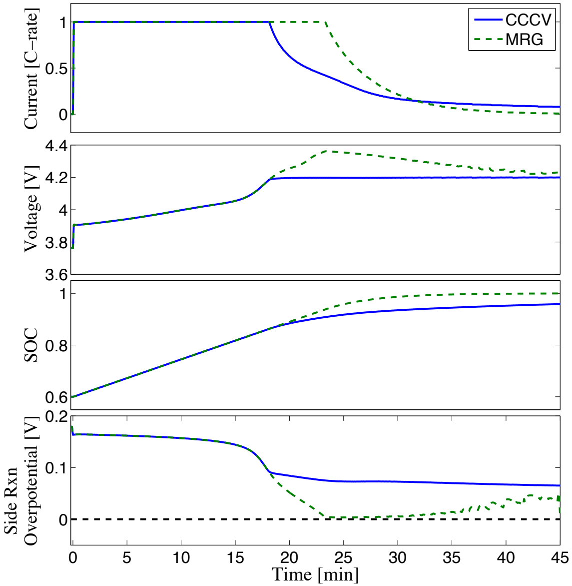


Application to Charging



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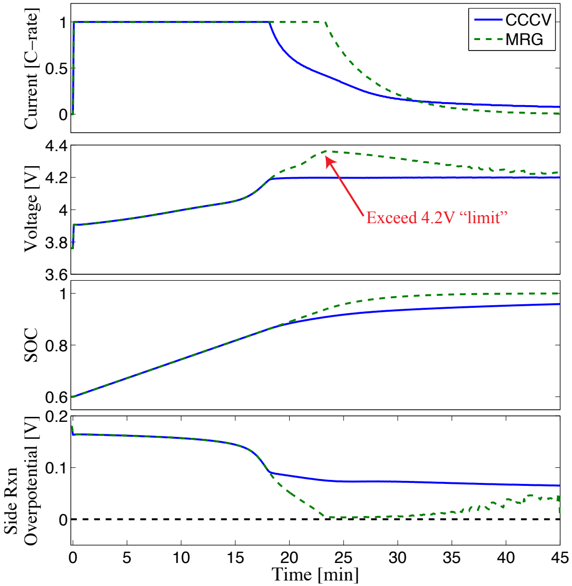

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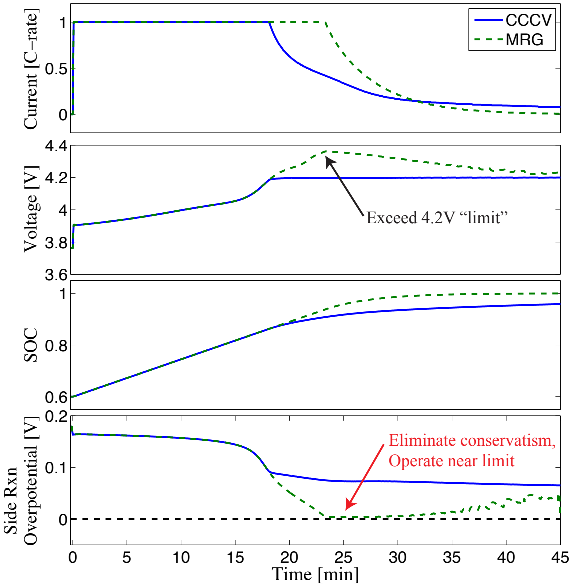

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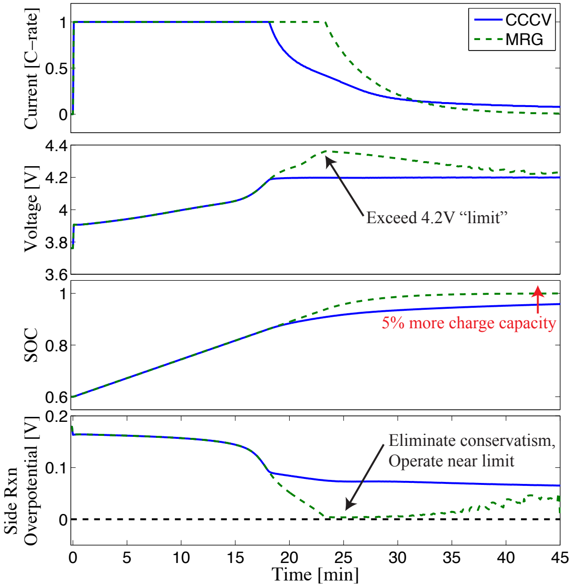

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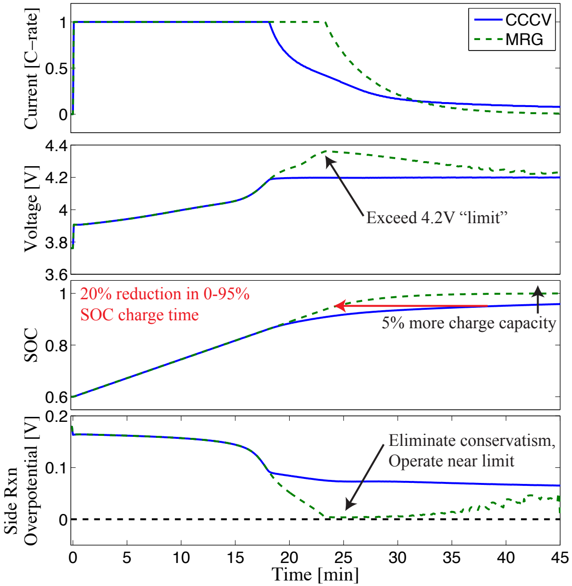


Outline

PHEV Power Management

Problem Statement

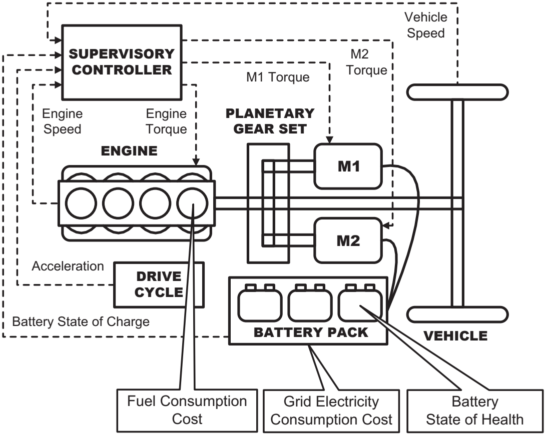
Design a supervisory control algorithm for plug-in hybrid electric vehicles (PHEVs) that splits engine and battery power in some optimal sense.

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 Optimal Control

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

$$c(x_k, u_k) = \alpha \cdot c_E(x_k, u_k) + (1-\alpha)\cdot c_H(x_k, u_k)$$

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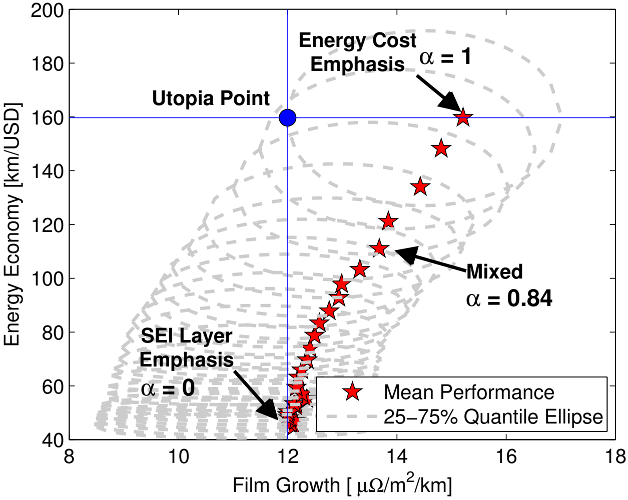
Energy: $$c_E(x_k, u_k) = \beta W_{fuel} + \frac{-V_{oc} Q_{batt} \dot{SOC}}{\eta_{EVSE}}$$

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

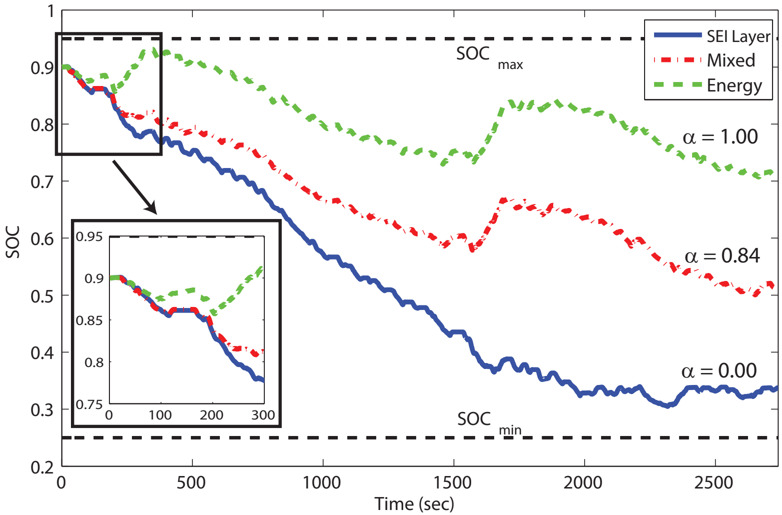
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth



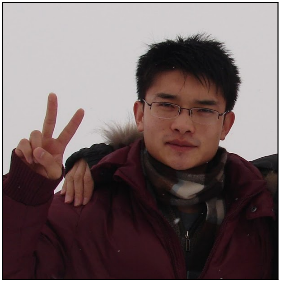
SOC Trajectories

Anode-side SEI Layer Growth | UDDSx2



Outline

Chao Sun



Ph.D. Candidate, Beijing Institute of Technology (since 9/2010)

Visiting Student Researcher, UC Berkeley (since 9/2012)

The Velocity Forecasting Problem

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

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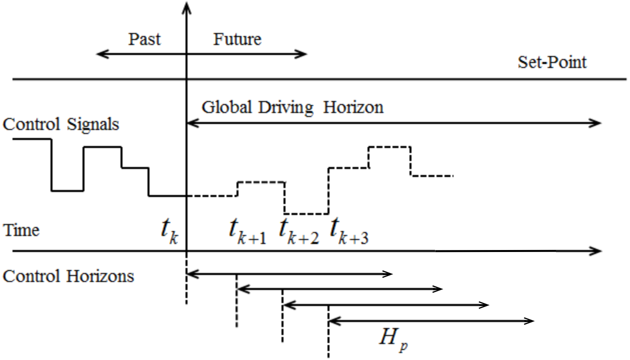
Consider Model Predictive Control (MPC)

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



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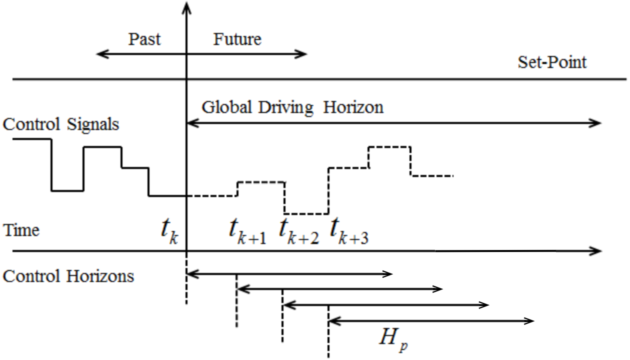
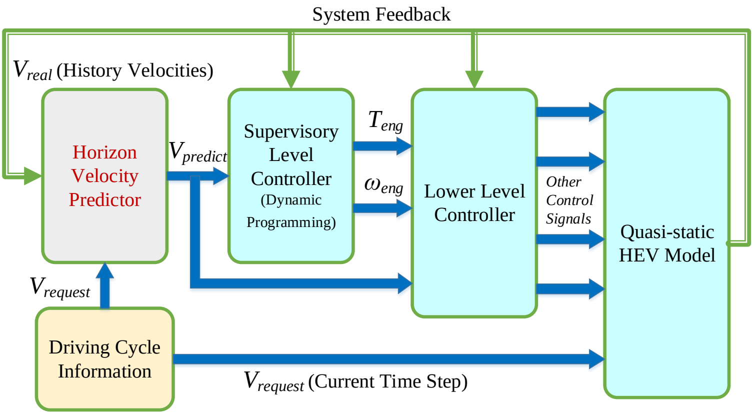


Punchline: Better velocity forecast produce better economy

MPC Energy Management w/ Velocity Prediction



Candidate Velocity Predictors

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

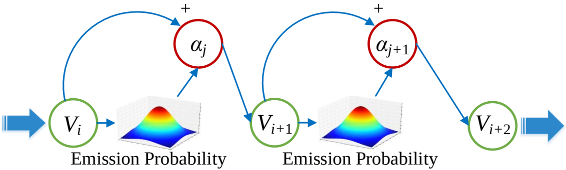
Candidate Velocity Predictors

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

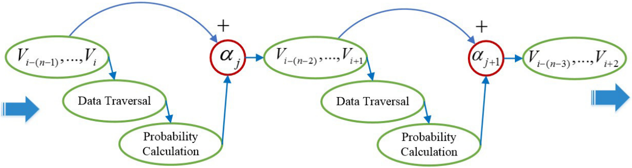
$$V_{k+n} = (1+\varepsilon)^n V_k, \text{ for } n = 1, 2, ..., H_p$$

Candidate Velocity Predictors

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



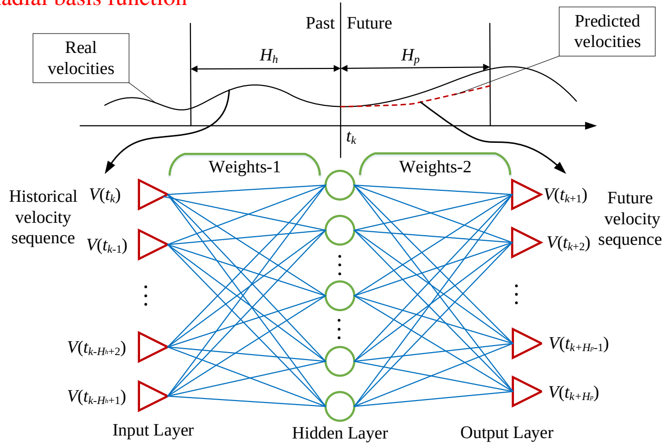
One-stage



Multi-stage

Candidate Velocity Predictors

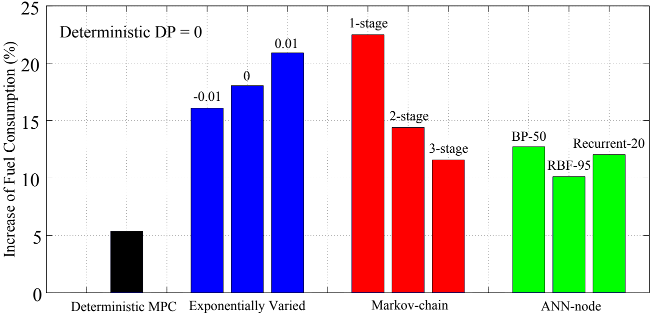
1. Generalized exponentially varying
2. Markov chain models
3. Artificial Neural Networks
    - Back propagation
    - Layer recurrent
    - Radial basis function

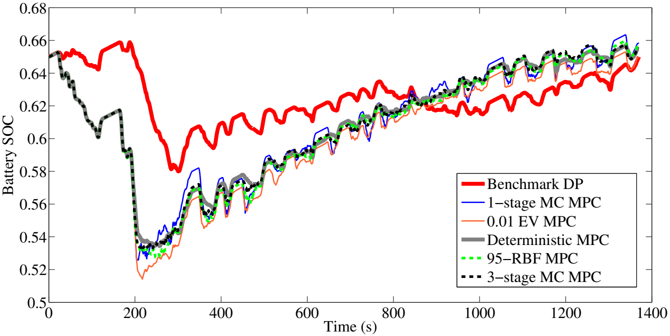


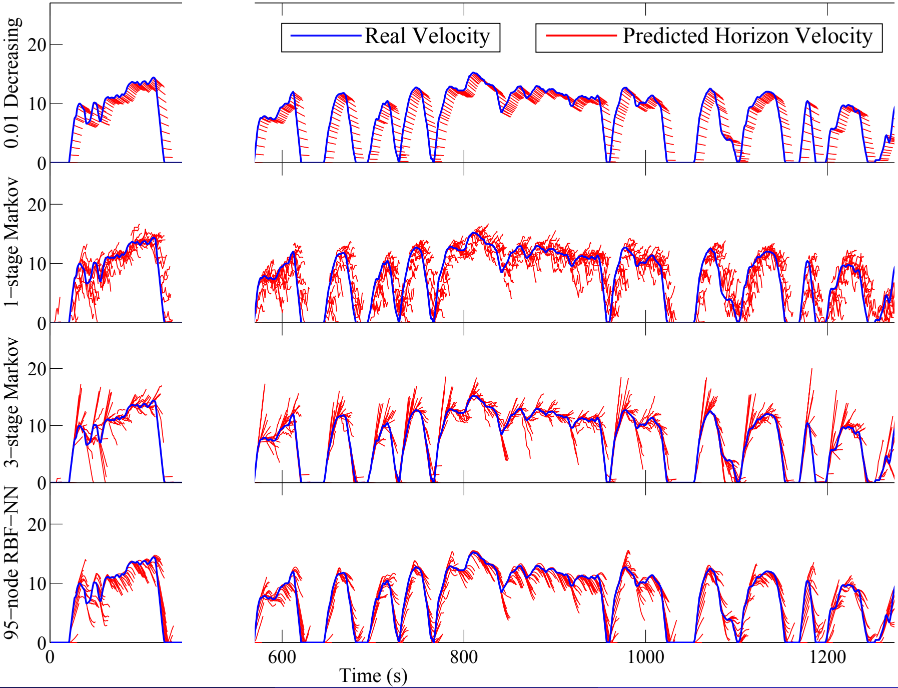
Comparison on UDDS

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 (%)
-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
Time (s)
Benchmark DP
1−stage MC MPC
0.01 EV MPC
Deterministic MPC
95−RBF MPC
3−stage MC MPC

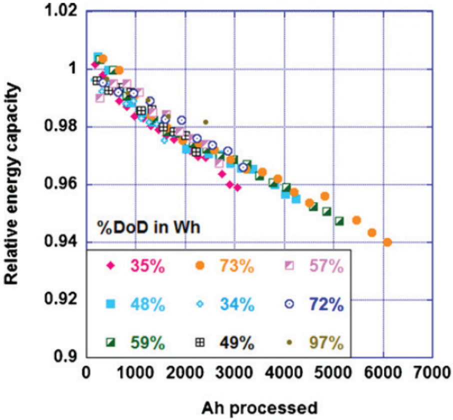


Real Velocity
Predicted Horizon Velocity
0.01 Decreasing
1−stage Markov
3−stage Markov
95−node RBF−NN
0
10
20
0
600
800
1000
1200
Time (s)

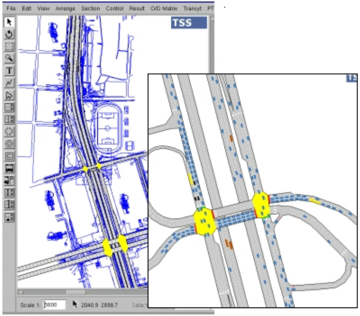
Outline

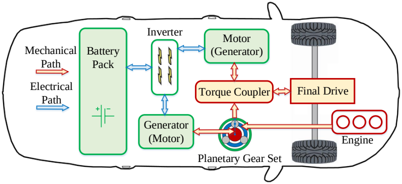
Opportunity 1: Monitoring & Control of Battery Aging

- Novel sensors
- Electrochemical model-based designs
- Mitigation strategies (health v. performance)



Opportunity 2: Closing-the-loop around Real-time Traffic Data

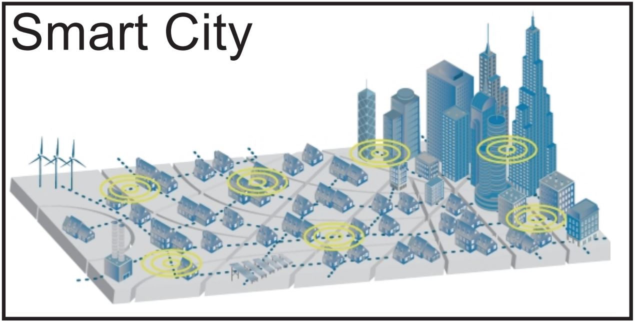




Real-time traffic monitoring → HEV/PEV Energy Management

Opportunity 3: Smart City Integration

- Smart Homes
- Smart Grid
- Smart Transportation



Xie Xie!

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