Adaptive Estimation and Control of Models for Battery Electrochemistry

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UC San Diego

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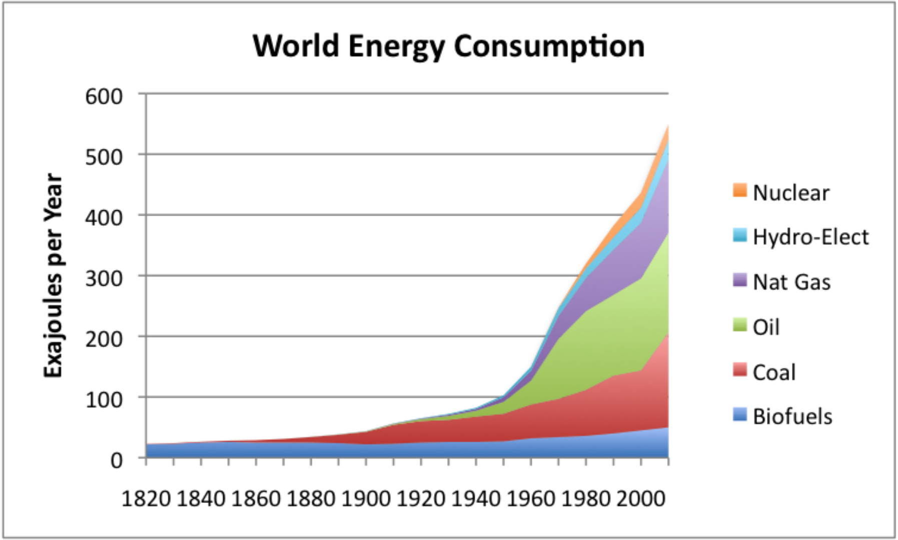
UCDAVIS
UNIVERSITY OF CALIFORNIA

Core Philosophy:

(Dynamical models of physical phenomena)

$+$ (novel control paradigms)

$=$ (transformative advancements)



Vaclav Smil Estimates from Energy Transitions

Energy Initiatives

Denmark 50% wind penetration by 2025

China leads manufacturing of renewable tech

Brazil uses 86% renewables

THE WHITE HOUSE
WASHINGTON

EV Everywhere

SunShot

Green Button

33% renewables by 2020

Go Solar California

20% reduction of bldg. energy by 2015

Energy Crisis Solutions

Integrate variable renewables	Decrease energy waste
$\Downarrow$	$\Downarrow$
Energy storage	Intelligent energy management
(e.g., batteries)	(e.g., smart grids)

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Outline

1. Batteries
   - [Electrochemical Modeling] Incorporating Physics
   - [SOC/SOH Estimation] Looking Inside w/ Models, Meas., and Math
   - [Constrained Control] Operate at the Limits, Safely
   - [PHEV Power Management] Max eMPG and Max Batt Life
2. Demand Response in Smart Grids
3. Future

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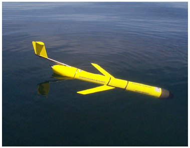
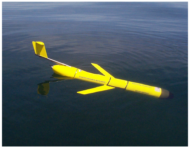
A Golden Era

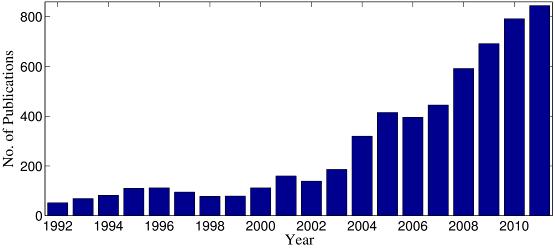

IS-1
ST. JUDE MEDICAL
Sylmar, CA USA
ACCENT SR RF
PM1210 SSR
IS-1
ST. JUDE MEDICAL
Sylmar, CA USA
ANTHEM RF
PM3212 DDDRV



A Golden Era



Keyword: “Battery Systems and Control”



The Battery Problem

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

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Today's reality: Expensive, conservatively design/operated, die too quickly

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Some Motivating Facts

EV Batts	\$800 / kWh now (2010) \$125 / 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)

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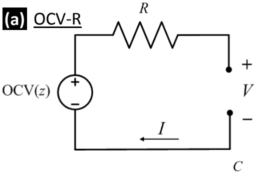
Equivalent Circuit Model

(a) OCV-R



Battery Models

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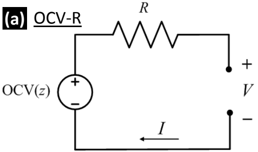
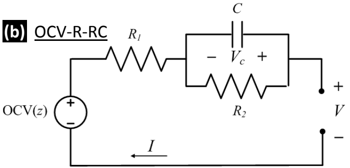
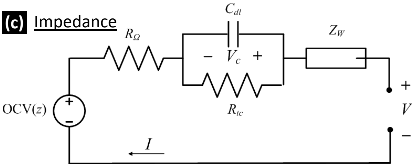


(b) OCV-R-RC



(c) Impedance



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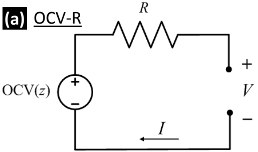

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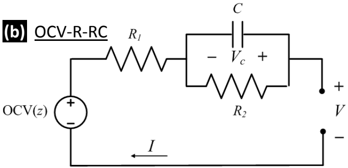

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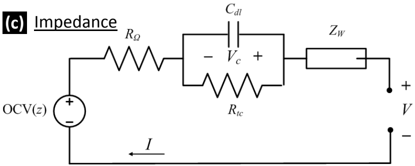
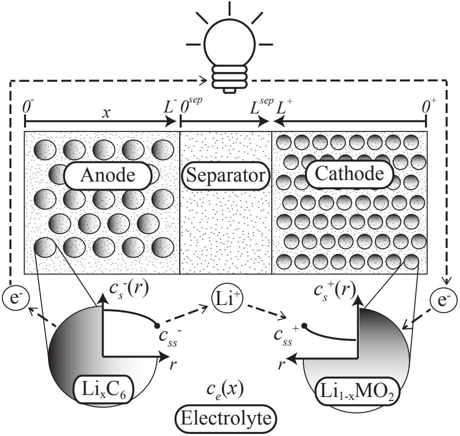
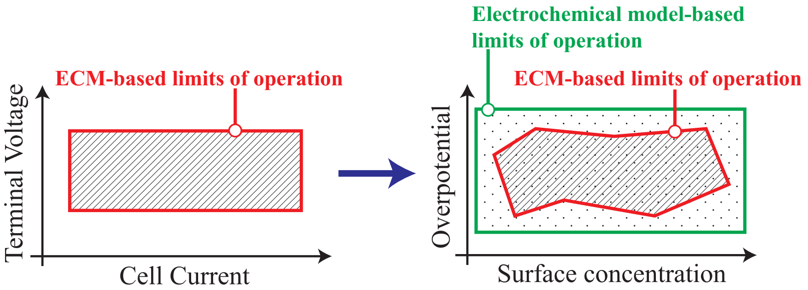


Electrochemical Model



Operate Batteries at their Physical Limits



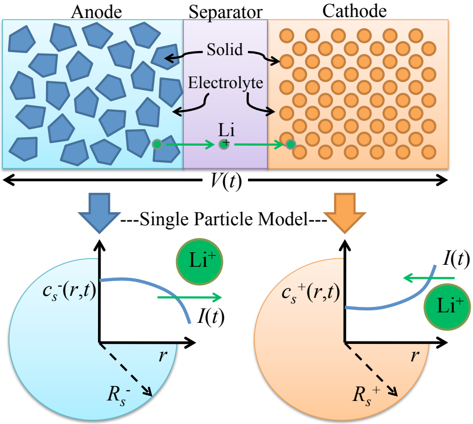
Electrochemical Model Equations

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

Single Particle Model (SPM)

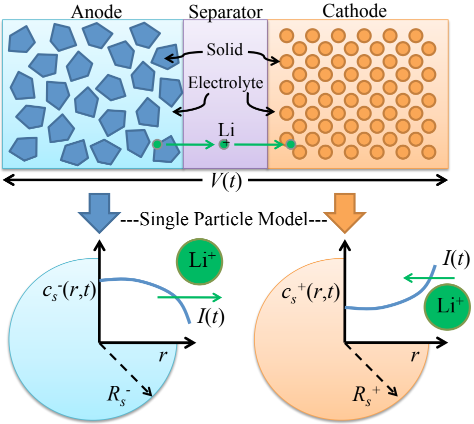


Single Particle Model (SPM)

Diffusion of Li in solid phase:

$$\frac{\partial c_s^-}{\partial t}(r,t) = \frac{D_s^-}{r^2}\frac{\partial}{\partial r}\left[r^2 \frac{\partial^2 c_s^-}{\partial r^2}(r,t)\right]$$

$$\frac{\partial c_s^+}{\partial t}(r,t) = \frac{D_s^+}{r^2}\frac{\partial}{\partial r}\left[r^2 \frac{\partial^2 c_s^+}{\partial r^2}(r,t)\right]$$



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Boundary conditions:

$$\frac{\partial c_s^-}{\partial r}(R_s^-,t) = -\rho^+ I(t)$$

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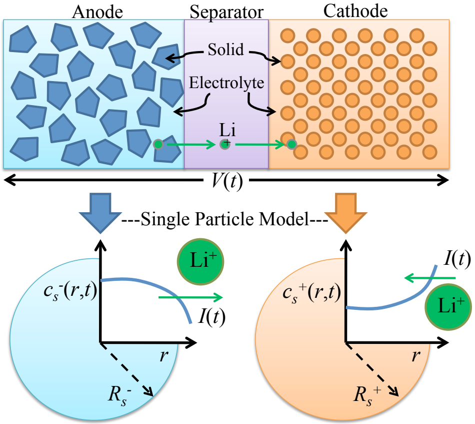

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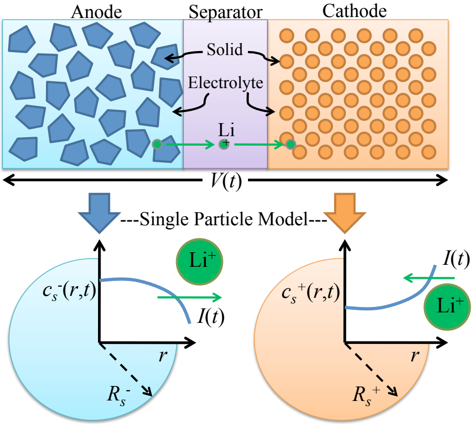
Voltage Output Function:

$$V(t) = h(c_{ss}^-(t), c_{ss}^+(t), I(t); \theta)$$



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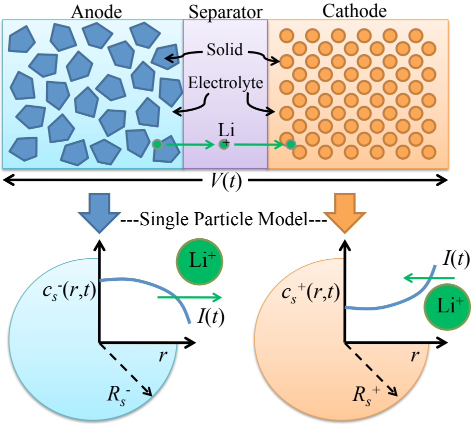

Definitions

- SOC: Bulk concentration SOC_{bulk}, Surface concentration $c_{ss}^-(t)$
- SOH: Physical parameters, e.g. ε, q, n_{Li}, R_f

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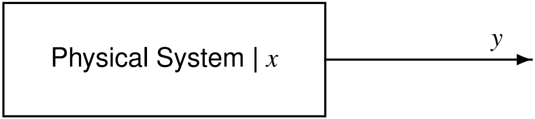
The SOC Estimation Problem

Problem Statement

Estimate states $c_s^-(r,t), c_s^+(r,t)$ from measurements $I(t), V(t)$ and SPM

Intro to Estimation



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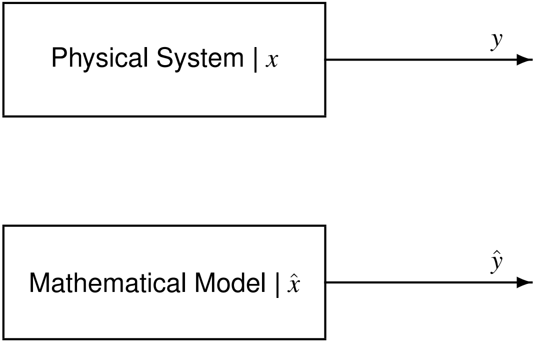

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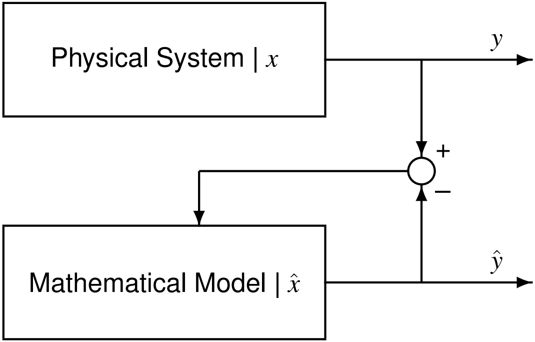

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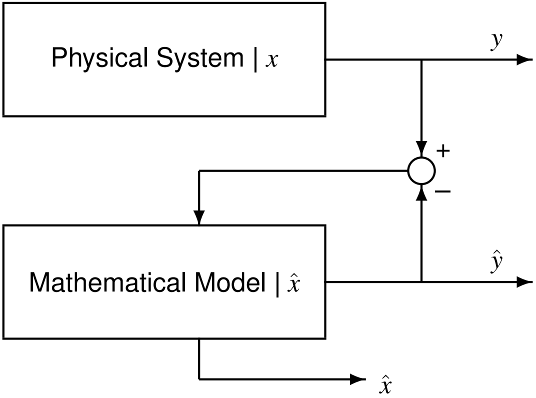

Backstepping PDE Estimator

Simplify the Math

- Model reduction to achieve observability
- Normalize time and space
- Scale spatial dimension

Backstepping PDE Estimator

Model Eqns. for Observer Design: $c(r,t)$

$$\begin{aligned} \frac{\partial c}{\partial t}(r,t) &= \varepsilon \frac{\partial^2 c}{\partial r^2}(r,t) && \text{Heat PDE} \\ c(0,t) &= 0 \\ \frac{\partial c}{\partial r}(1,t) - c(1,t) &= -q\rho I(t) \\ \text{Measurement} &= c(1,t) = \check{c}_{ss}^{-}(t) \end{aligned}$$

Backstepping PDE Estimator

Estimator: $\hat{c}(r,t)$

$$
\begin{aligned}
\frac{\partial \hat{c}}{\partial t}(r,t) &= \varepsilon \frac{\partial^2 \hat{c}}{\partial r^2}(r,t) + p_1(r)\left[c(1,t) - \hat{c}(1,t)\right] \\
\hat{c}(0,t) &= 0 \\
\frac{\partial \hat{c}}{\partial r}(1,t) - \hat{c}(1,t) &= -q\rho I(t) + p_{10}\left[c(1,t) - \hat{c}(1,t)\right]
\end{aligned}
$$

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\end{aligned}$$

Estimation Error Dynamics: $\tilde{c}(r,t) = c(r,t) - \hat{c}(r,t)$

$$\begin{aligned}
\frac{\partial \tilde{c}}{\partial t}(r,t) &= \varepsilon \frac{\partial^2 \tilde{c}}{\partial r^2}(r,t) - p_1(r)\tilde{c}(1,t) \\
\tilde{c}(0,t) &= 0 \\
\frac{\partial \tilde{c}}{\partial r}(1,t) - \tilde{c}(1,t) &= -p_{10}\tilde{c}(1,t)
\end{aligned}$$

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\end{aligned}$$

The Concept

$$\tilde{c}(r,t) = \tilde{w}(r,t) - \int_r^1 p(r,s)\tilde{w}(s)ds$$ Backstepping Transformation

$$\frac{\partial \tilde{w}}{\partial t}(r,t) = \varepsilon \frac{\partial^2 \tilde{w}}{\partial r^2}(r,t) + \lambda \tilde{w}(r,t)$$ Exp. Stable Target System

$$\tilde{w}(0,t) = 0$$

$$W(t) = \frac{1}{2}\int_0^1 \tilde{w}^2(x,t)dx$$

$$\frac{\partial \tilde{w}}{\partial r}(1,t) = \frac{1}{2}\tilde{w}(1,t)$$

$$\dot{W}(t) \leq -\gamma W(t)$$

Backstepping PDE Estimator

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Kernel PDE

$$p(r,s) : \mathcal{D} \to \mathbb{R}, \qquad \mathcal{D} = \{(r,s) | 0 \le r \le s \le 1\}$$

$$p_{rr}(r,s) - p_{ss}(r,s) = \frac{\lambda}{\varepsilon} p(r,s) \qquad p_1(r) = -p_s(r,1) - \frac{1}{2} p(r,1)$$

$$p(0,s) = 0 \qquad p_{10} = \frac{3 - \lambda/\varepsilon}{2}$$

$$p(r,r) = \frac{\lambda}{2\varepsilon} r$$

Backstepping PDE Estimator

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\end{aligned}
$$

Explicit Solution to Estimator Gains

$$
p_1(r) = \frac{-\lambda r}{2\varepsilon z}\left[I_1(z) - \frac{2\lambda}{\varepsilon z} I_2(z)\right] \qquad \text{where} \quad z = \sqrt{\frac{\lambda}{\varepsilon}(r^2 - 1)}
$$

$$
p_{10} = \frac{1}{2}\left(3 - \frac{\lambda}{\varepsilon}\right)
$$

The SOH Estimation Problem

Problem Statement

Estimate physical parameters from measurements $I(t), V(t)$ and SPM

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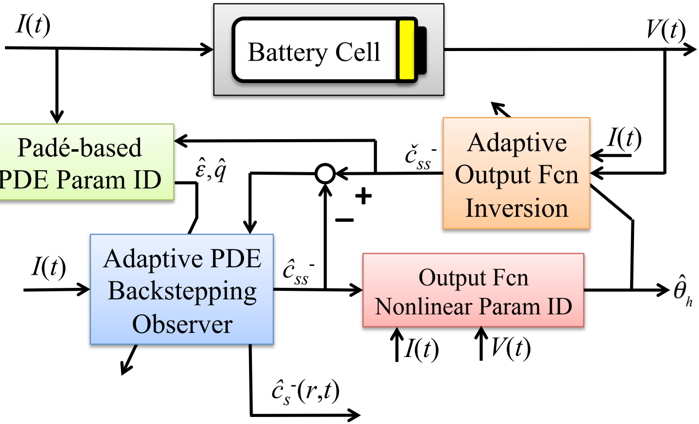
Estimate physical parameters from measurements $I(t), V(t)$ and SPM

Relate uncertain parameters to SOH-related concepts

- Capacity fade
- Power fade

Adaptive Observer

Combined State & Parameter Estimation



Output Function Nonlinear Parameter ID

Nonlinearly Parameterized Output

$$V(t) = h(c_{ss}^{-}(t), I(t); \theta)$$

- θ contains many parameters
- Linear dependence b/w parameters?

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Identifiability Analysis

- Linearly independent parameter subset : $\theta_h = [n_{Li}, R_f]^T$
  - n_{Li} : Moles of cyclable Li (Capacity Fade)
  - R_f : Resistance of current collectors, electrolyte, etc. (Power Fade)

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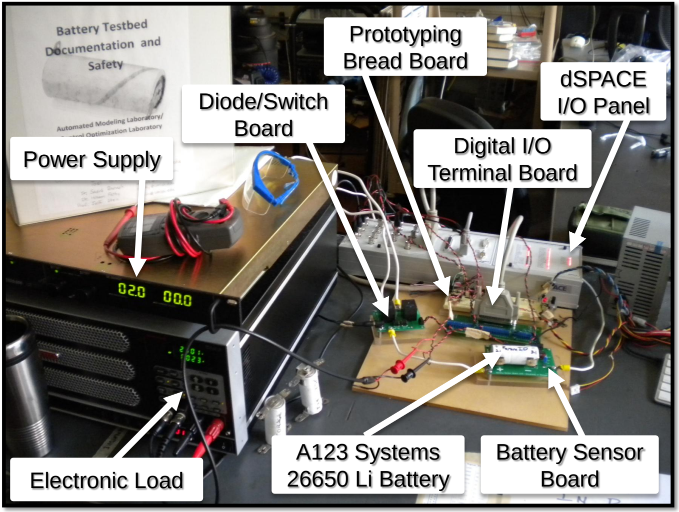
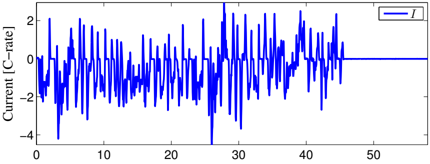
Apply nonlinear recursive least squares to θ_h

Custom-Built Battery-in-the-Loop Testbed



Results

UDDS Drive Cycle Input



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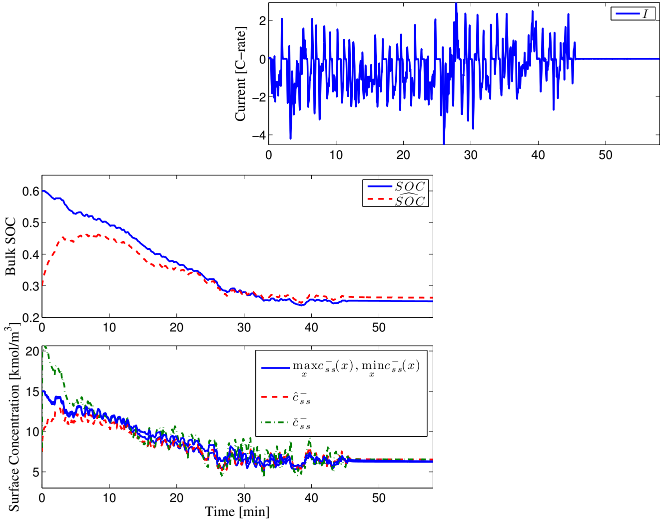

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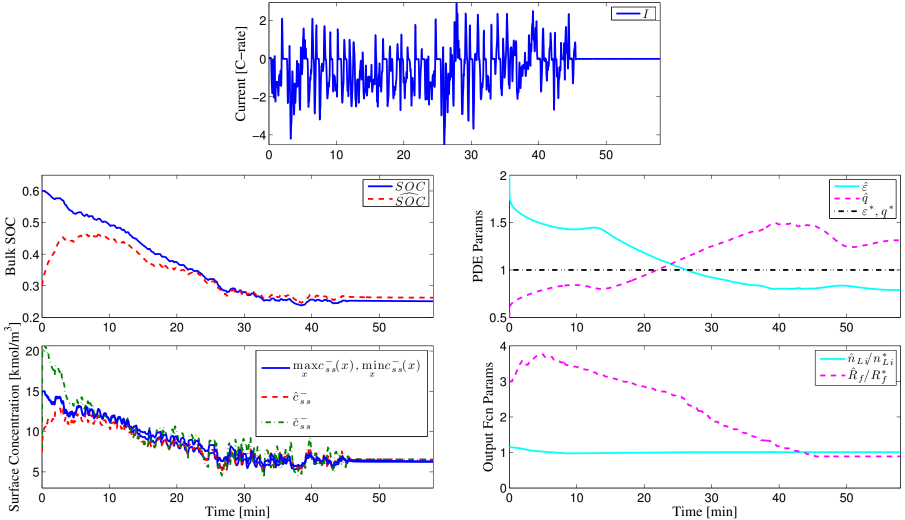
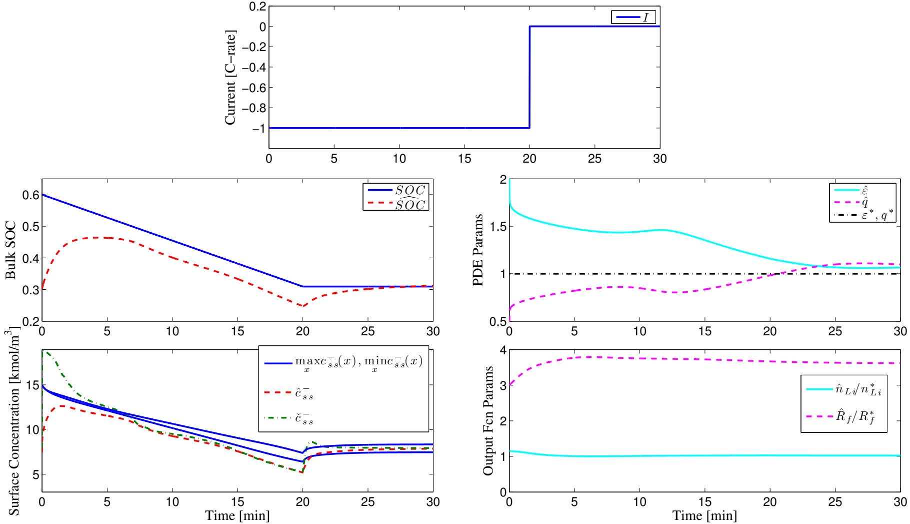


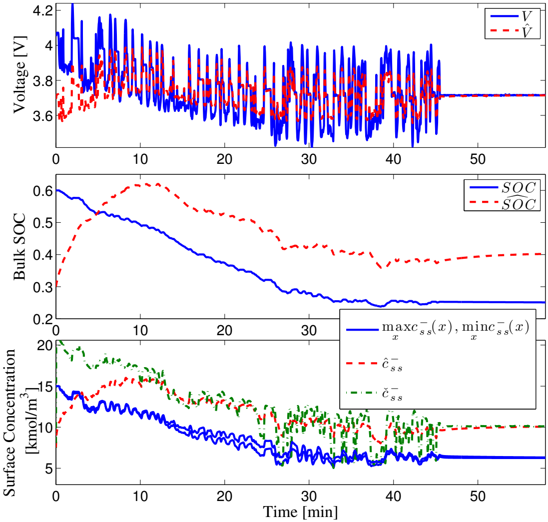
Results

Constant 1C Discharge

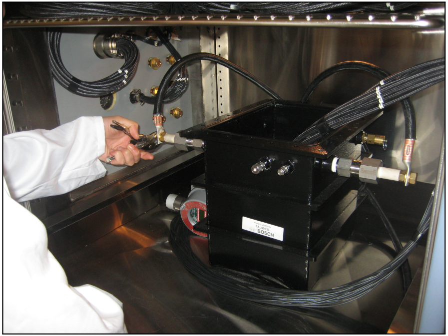


Results

No Parameter Adaption - Bias in State Estimates



Experimental Testing | ARPA-E AMPED Program



arpa·e BOSCH COBASYS

Outline

1. Batteries
   - [Electrochemical Modeling] Incorporating Physics
   - [SOC/SOH Estimation] Looking Inside w/ Models, Meas., and Math
   - [Constrained Control] Operate at the Limits, Safely
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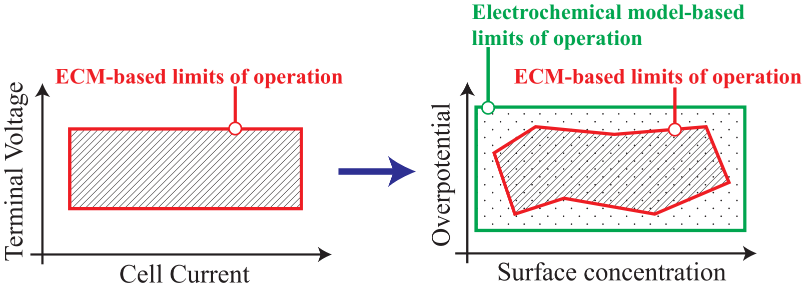
Operate Batteries at their Physical Limits

Operate Batteries at their Physical Limits

Problem Statement

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

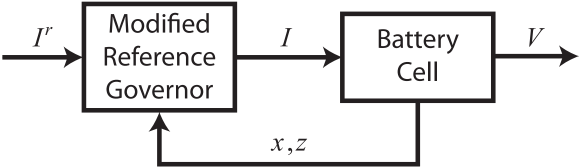


Constraints

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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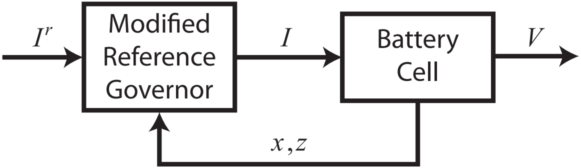

MRG Equations

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

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

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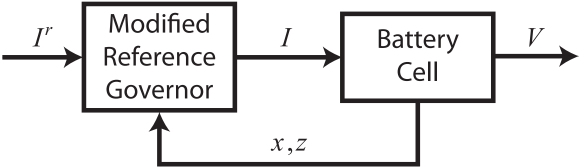

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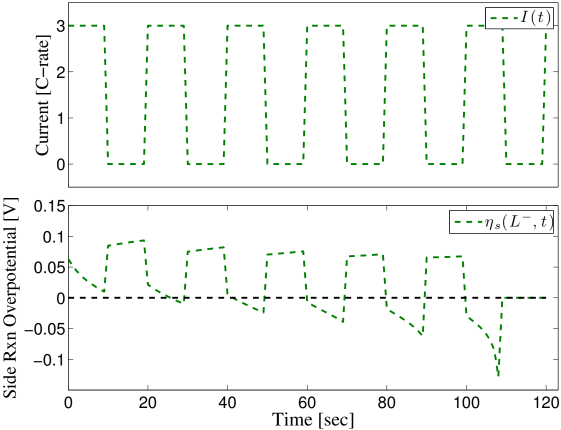
Def'n: Admissible Set $\mathcal{O}$

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

Constrained Control of EChem States



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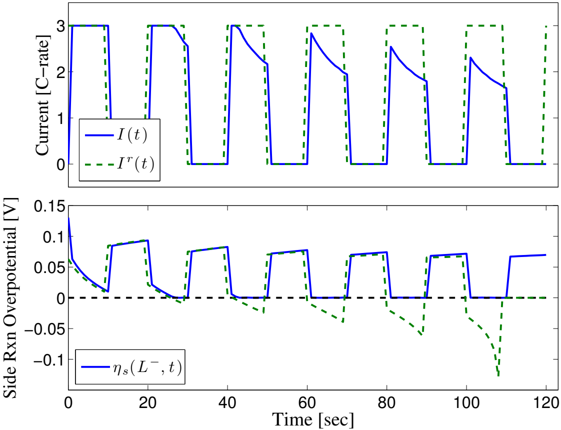
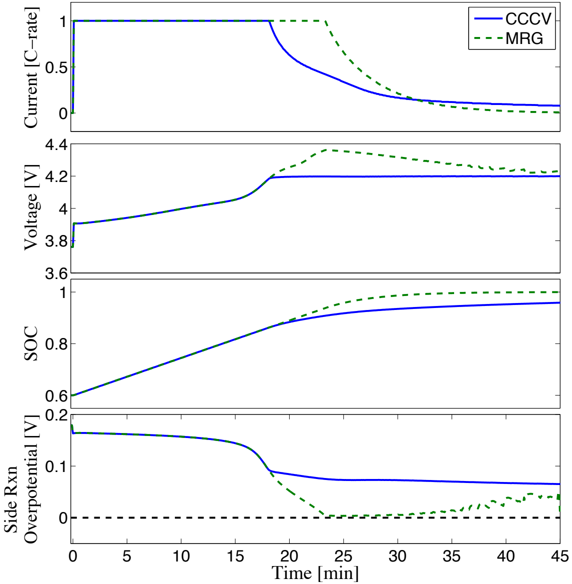


Application to Charging



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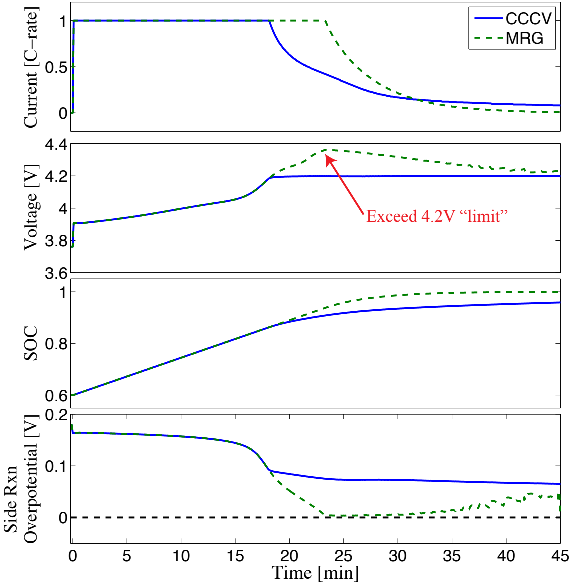

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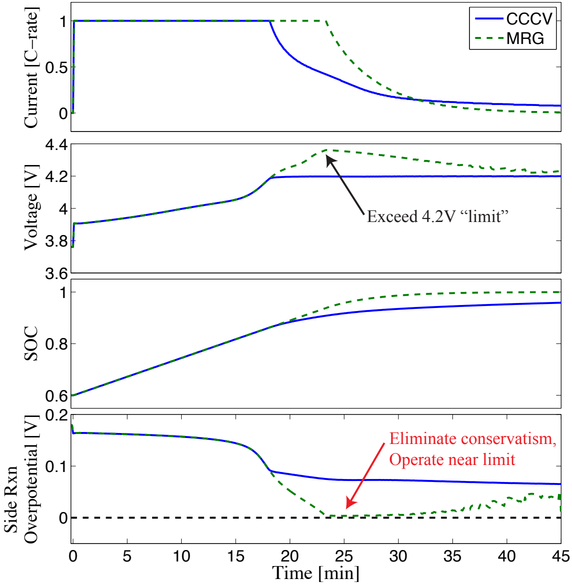

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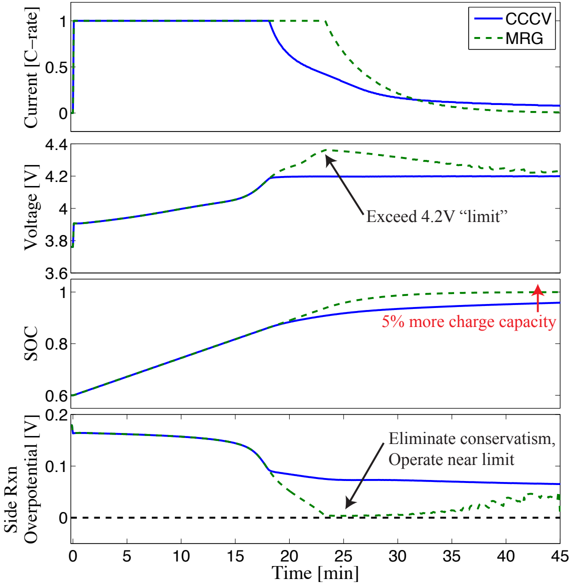

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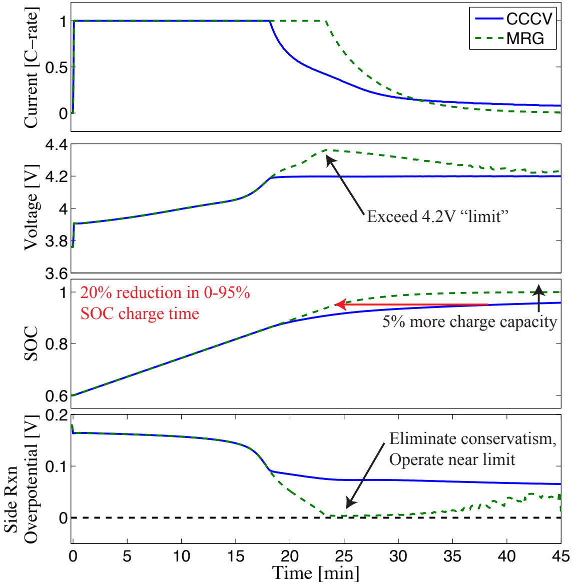

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PHEV Power Management

Problem Statement

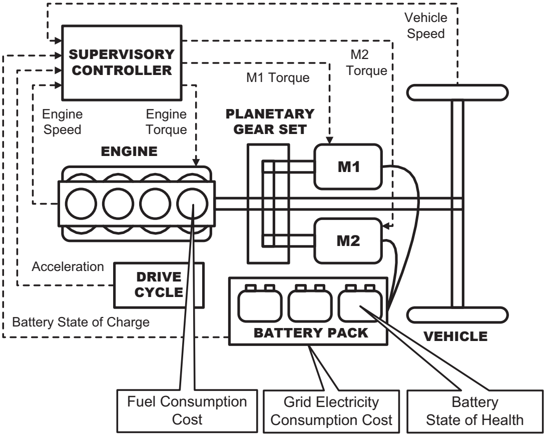
Design a supervisory control algorithm for plug-in hybrid electric vehicles (PHEVs) that splits engine and battery power in some optimal sense.

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

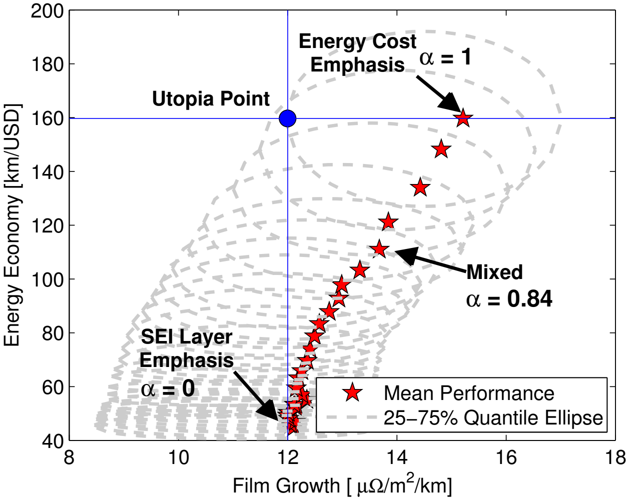
- Control Inputs
  - Engine Torque
  - M1 Torque
- State Variables
  - Engine speed
  - Vehicle speed
  - Battery SOC
  - Vehicle acceleration (Markov Chain)



Control Optimization: Minimize energy consumption cost AND battery aging

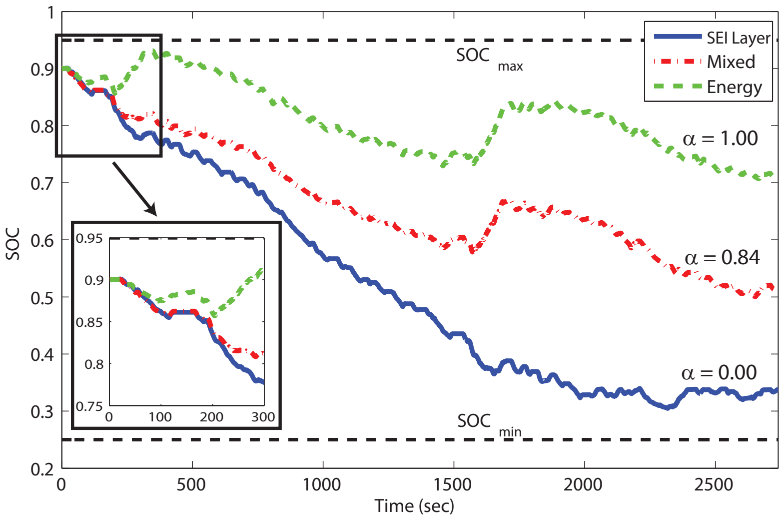
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth



SOC Trajectories

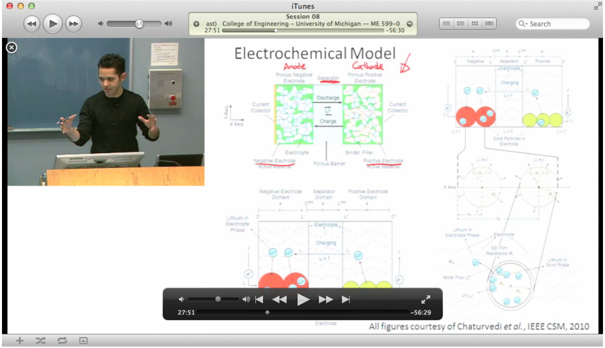
Anode-side SEI Layer Growth | UDDSx2



Enrollment

- Winter 2010: 59 + 5 distance
- Winter 2011: 50 + 26 distance
- ME, EE, ChemE, CS, Energy Systems, MatSci, Physics, Math

- Undergraduates
- Graduate students
- Professionals
  - Tesla Motors, General Motors, Roush, US Army



Summary of Contributions

Simultaneous SOC/SOH estimation
of physically meaningful variables via electrochemical models,
PDE estimation theory, and adaptive control.

Constrained control of batteries
via an electrochemical model
and reference governors.

PHEV power management
using electrochemical models
and stochastic optimal control.

Impact through education.

Energy Crisis Solutions

Integrate variable renewables	Decrease energy waste
$\Downarrow$	$\Downarrow$
Energy storage	Intelligent energy management
(e.g., batteries)	(e.g., smart grids)

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Energy storage

(e.g., batteries)

Decrease energy waste

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Needs: 33% renewables in CA by 2020

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Some Interesting Facts

Thermostatically Controlled Loads (TCLs)	50% of U.S. electricity consumption is TCLs 11% of thermostats are programmed Comfort is loosely coupled with control

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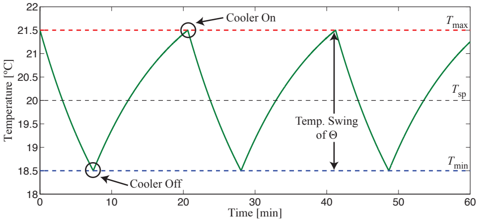
The Punchline

Flexible loads (e.g. TCLs) can absorb variability in renewable generation

Modeling Aggregations of TCLs

Individual TCL models
$\Downarrow$
(Tens of) Thousands of hybrid ODEs



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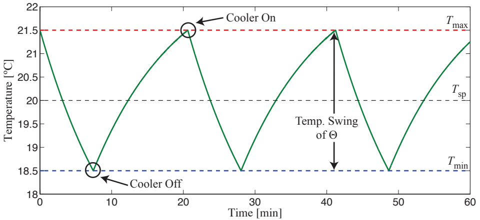
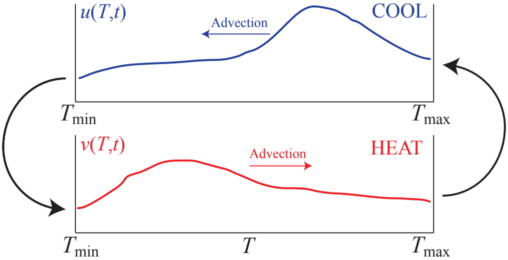


Model **aggregations** of TCLs

$\Downarrow$

Two coupled linear PDEs



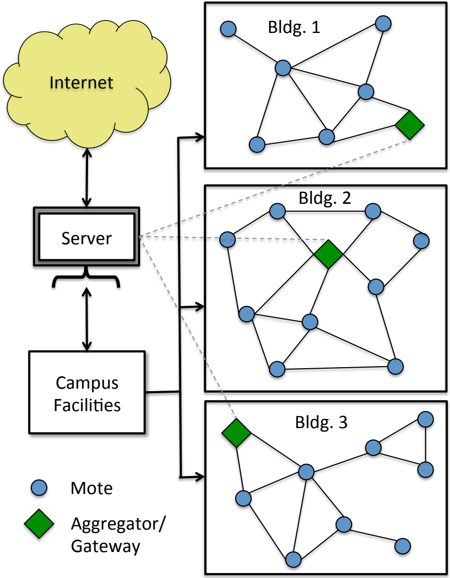
$u(T,t)$	# TCLs/°C, in COOL state, @ temp T, time t
$v(T,t)$	# TCLs/°C, in HEAT state, @ temp T, time t

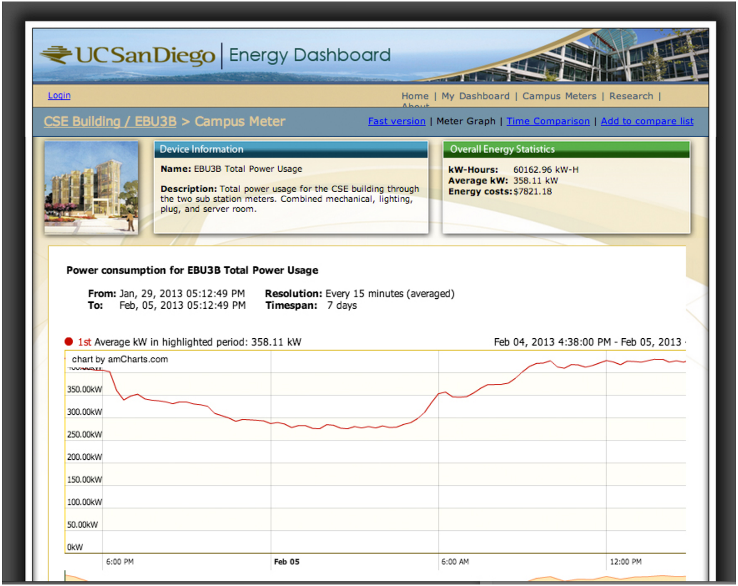
UCSD Campus: A Living Laboratory

Goal: Smart Campus

1. Deploy temp. wireless sensor network
2. Verify models and estimation algorithms
3. Derive control algorithms
4. Implement via UCSD facilities & management

Libelium Waspmotes and Meshlium Gateway





energy.ucsd.edu

Fuse data from Dr. Yuvraj Agarwal's Energy Dashboard project

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Future: EChem-based Battery Management Systems

Vision: Enhanced energy, power, chg times, life from existing batts.

Open technical problems for BMS:
(1) State observability

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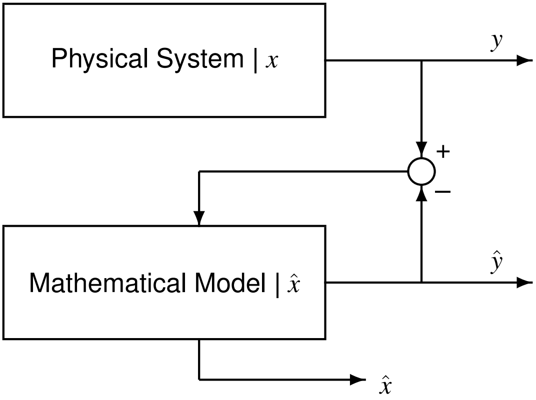

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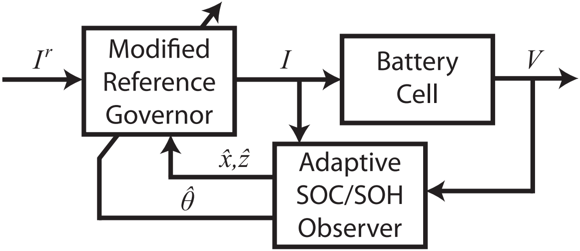

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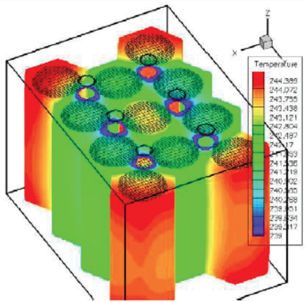
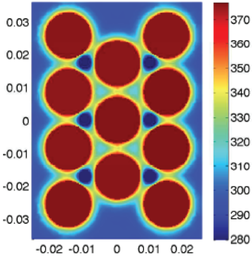


CFD simulation



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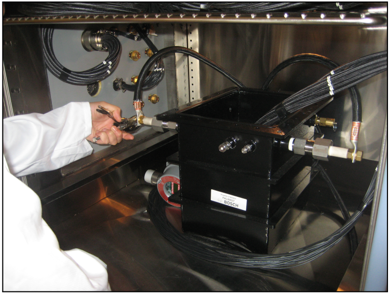

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- ARPA-E AMPED
- DoD HESM

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Goal: Solve range anxiety

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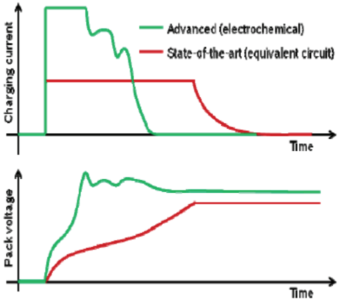

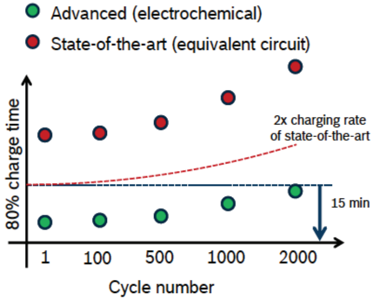

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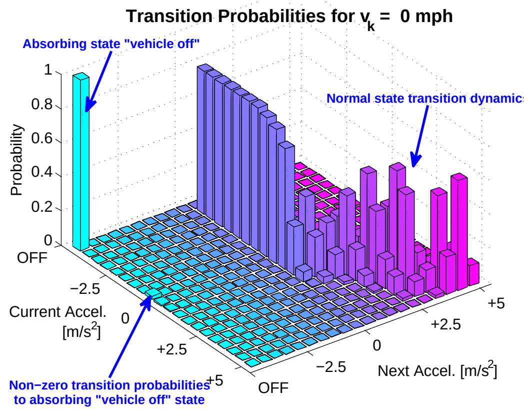
(2) Self-Learning Driving Patterns

Adaptive Markov chain model: $p_{ijm} = \Pr\left(a_{k+1} = j | a_k = i, v_k = m\right)$



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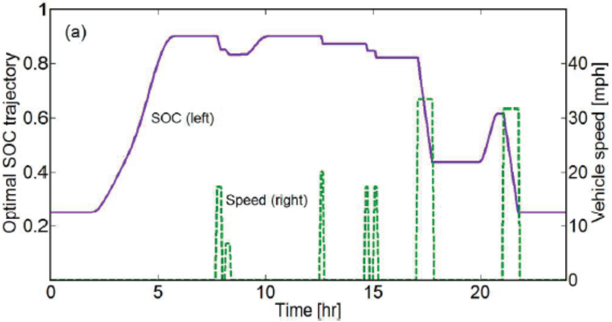
(3) Optimal EV Usage

- Satisfy range req.
- Max health, min energy consumption
- Grid interface for city-wide resilience



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$$
\begin{aligned}
u_t(x,t) &= \alpha\lambda(x)u_x + \alpha u + \beta u_{xx} \\
v_t(x,t) &= -\alpha\mu(x)v_x + \alpha v + \beta v_{xx} \\
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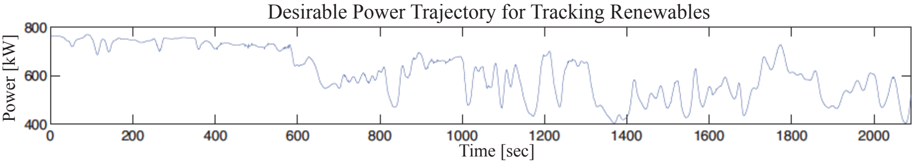

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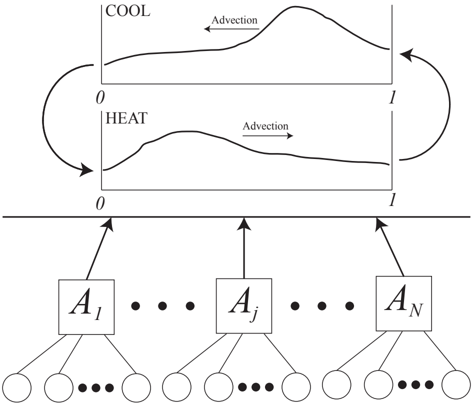
(3) Hierarchical Control Architecture



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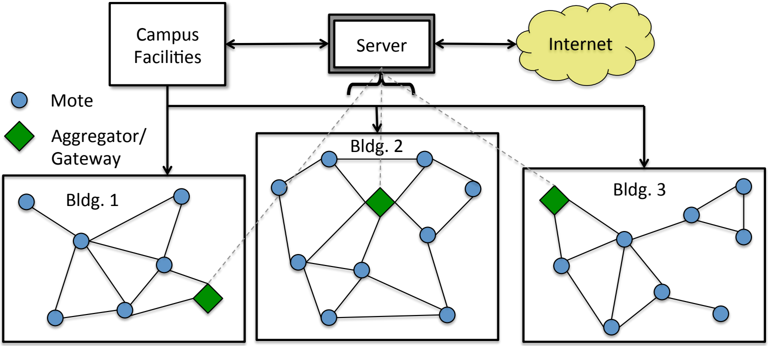

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Funding:

- California Energy Commission
- NSF EPAS, CPS

Courses I could teach

Undergrad

MAE 154 - Mechatronics
MAE 171 - Analysis, Simulation and Design of Mechatronic Systems
MAE 172 - Automatic Control of Engineering Systems

Graduate

MAE 218 - Advanced Energy Systems
MAE 272 - Theory and Design of Control Systems
MAE 274 - Analysis and Design of Digital Control Systems

Themes: Energy | Control systems

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Key Tools:

- PDE modeling
- Lyapunov stability
- Adaptive control
- Optimization

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Theory/Computational 70%	30% Experimental

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Energy Systems and Control Laboratory

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Outreach, Diversity, and Inclusion

- SHPE, NSBE, SWE
- C-STEM, UC LEADs

Publications available at http://flyingv.ucsd.edu/smoura/
smoura@ucsd.edu

Managing Overparameterization

$$\hat{\theta}_{pde} = \left[\begin{array}{c} \widehat{q\varepsilon^2} \\ \widehat{q\varepsilon} \\ \hat{\varepsilon} \end{array} \right] \longrightarrow \left[\begin{array}{c} \hat{\varepsilon} \\ \hat{q} \end{array} \right] = \hat{\theta}_{\varepsilon q}$$

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$$\begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \log \hat{\varepsilon} \\ \log \hat{q} \end{bmatrix} = \begin{bmatrix} \log\left(\widehat{q\varepsilon^2}\right) \\ \log\left(\widehat{q\varepsilon}\right) \\ \log\left(\hat{\varepsilon}\right) \end{bmatrix}$$

$$\begin{aligned} A_{\varepsilon q} \log(\hat{\theta}_{\varepsilon q}) &= \log(\hat{\theta}_{pde}) \\ \log(\hat{\theta}_{\varepsilon q}) &= A_{\varepsilon q}^{+} \log(\hat{\theta}_{pde}) \end{aligned}$$

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$$\hat{\theta}_{pde} = \begin{bmatrix} \widehat{q\varepsilon^2} \\ \widehat{q\varepsilon} \\ \hat{\varepsilon} \end{bmatrix} \longrightarrow \begin{bmatrix} \hat{\varepsilon} \\ \hat{q} \end{bmatrix} = \hat{\theta}_{\varepsilon q}$$

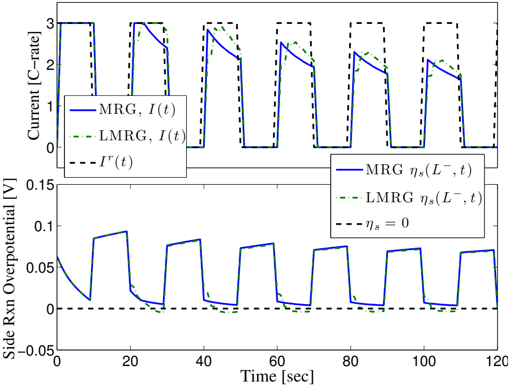
$$\begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \log \hat{\varepsilon} \\ \log \hat{q} \end{bmatrix} = \begin{bmatrix} \log \left(q\hat{\varepsilon}^2 \right) \\ \log \left(\hat{q\varepsilon} \right) \\ \log \left(\hat{\varepsilon} \right) \end{bmatrix}$$

$$\begin{aligned} A_{\varepsilon q} \log(\hat{\theta}_{\varepsilon q}) &= \log(\hat{\theta}_{pde}) \\ \log(\hat{\theta}_{\varepsilon q}) &= A_{\varepsilon q}^{+} \log(\hat{\theta}_{pde}) \end{aligned}$$

Remark: $A_{\varepsilon q}^{+} = \left(A_{\varepsilon q}^{T} A_{\varepsilon q} \right)^{-1} A_{\varepsilon q}^{T}$ is the Moore-Penrose psuedoinverse of $A_{\varepsilon q}$

Linear Reference Governor

Modified Reference Governor (MRG) : Simulations
Linearized MRG (LMRG) : Explicit function evaluation



PHEV Power Management

Problem Statement

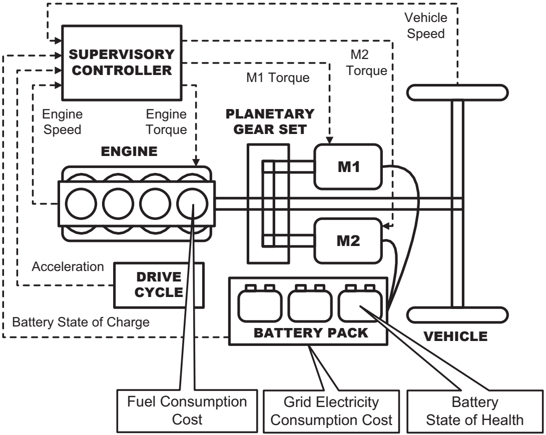
Design a supervisory control algorithm for plug-in hybrid electric vehicles (PHEVs) that splits engine and battery power in some optimal sense.

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

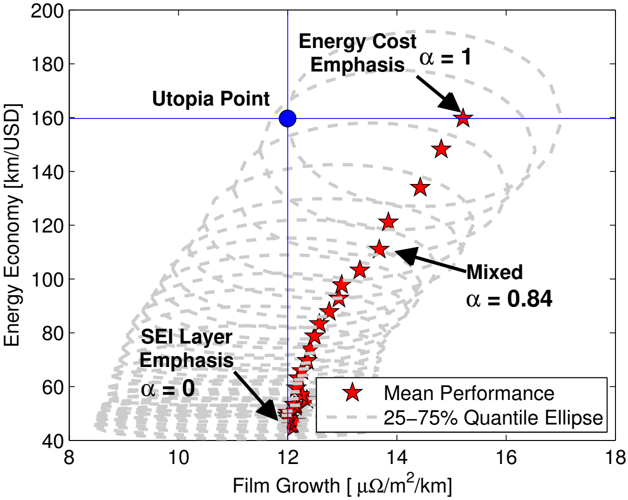
- Control Inputs
  - Engine Torque
  - M1 Torque
- State Variables
  - Engine speed
  - Vehicle speed
  - Battery SOC
  - Vehicle acceleration (Markov Chain)



Control Optimization: Minimize energy consumption cost AND battery aging

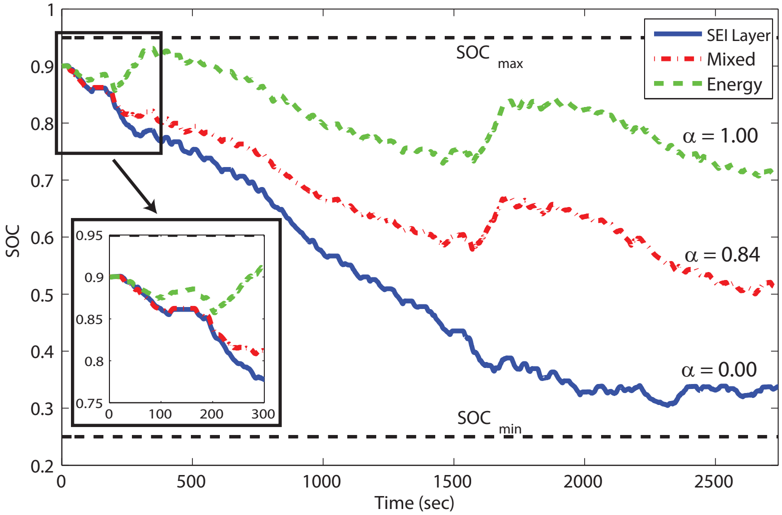
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth

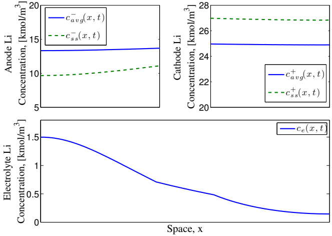


SOC Trajectories

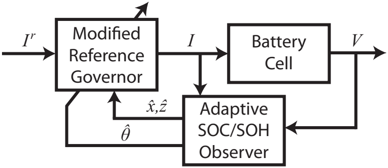
Anode-side SEI Layer Growth | UDDSx2



State Estimation w/ Electrolyte



Estimator + Reference Governor



Optimal charge/discharge

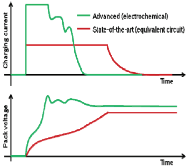


Figure 2: Charging phase of each duty cycle for BMS validation

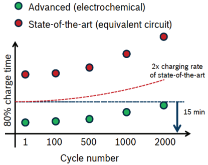
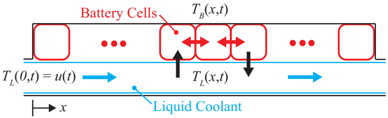


Figure 3: Comparison of charging time on a cycle to cycle basis for conventional BMS and advanced BMS

Thermal Management



Optimal Control of Distributed Parameter Systems

Models

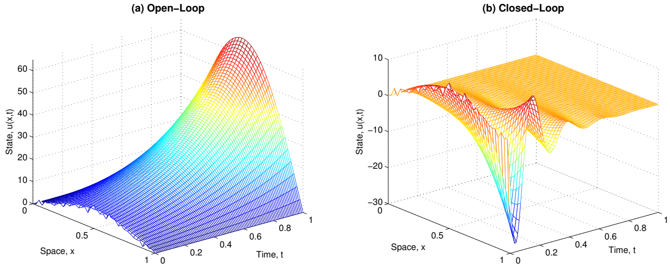
- Diffusion-Reaction-Advection
- Transport, Delays
- Waves, Beams, Nonlinear
- ...

Apps

- Fluid Dynamics
- Contaminant transport
- Solar Forecasting
- Heat Transfer
- ...

Control Results

- LQR
- Reference tracking
- Estimation
- Acutator/Sensor placement
- ...



Demand Response of Aggregated Storage

Joint Work with Jan Bendsten, Aalborg University, Denmark