Unleashing the Battery

Control Theoretic Solutions for Battery Management Systems

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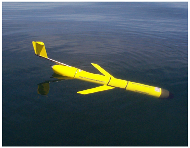
Princeton University

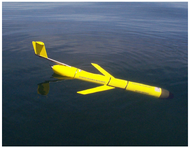
A Golden Era


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

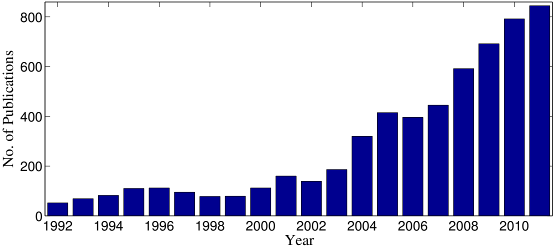



A123 SYSTEMS
2MWH-APU
HYBRID ANCILLARY POWER UNIT

A Golden Era



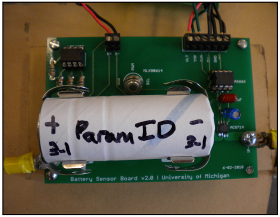
Keyword: “Battery Systems and Control”



Open Problems in Battery Systems and Control

Cell Level

- Modeling
- Design
- SOC/SOH Estimation
- ...



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- Change (Un)balancing
- Thermal Management
- Energy Management
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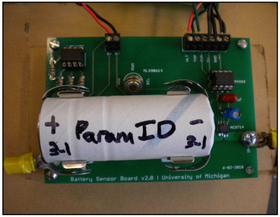

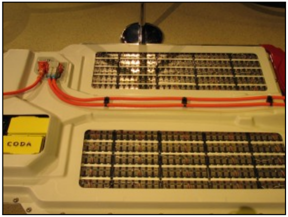

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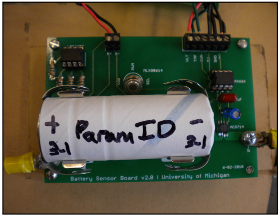
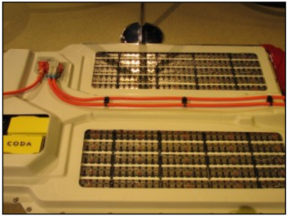
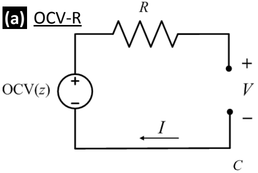
Smart-Grid Level

- Renewable Energy Integration
- Optimal Power Flow
- PEV Power Management
- ...





Equivalent Circuit Model



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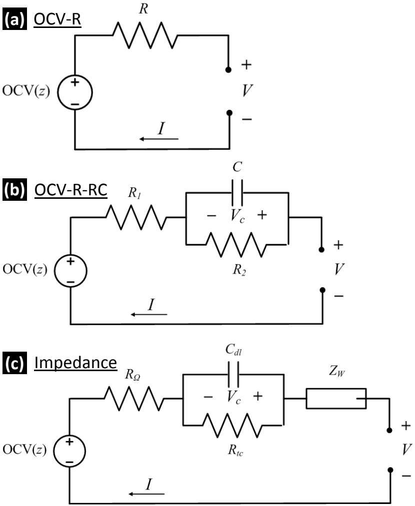
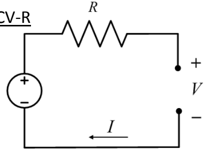
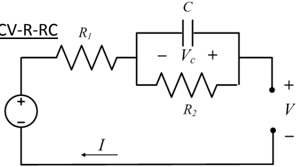


Equivalent Circuit Model

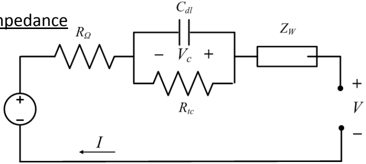
(a) OCV-R



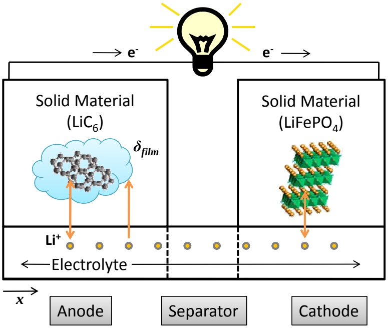
(b) OCV-R-RC



(c) Impedance



Electrochemical Model



Outline

1. SOC/SOH Estimation
   - Single Particle Model
   - State Estimation via PDE Backstepping
   - Parameter Identification via Adaptive & Nonlinear Control
   - Testing
2. PHEV Power Management
   - Models
   - Stochastic Optimal Control
   - Sample Results

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A Short History

- Equivalent Circuit Model

- Electrochemical Model

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- Equivalent Circuit Model
  - G. Plett (2004) - Extended Kalman Filter (States & Params)
  - RLS, Bias-correcting RLS, EKF on Impedance-based ECMs, LPV, Neural nets, Sliding-mode, Particle filters, and many more...
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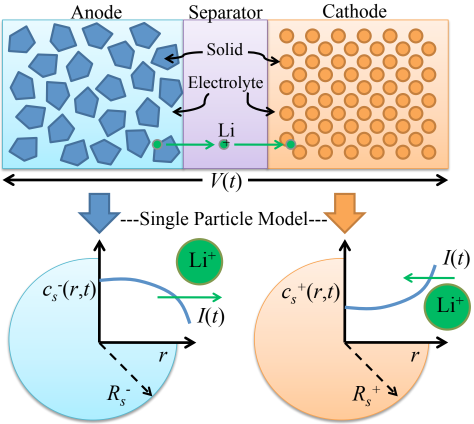
Single Particle Model (SPM)



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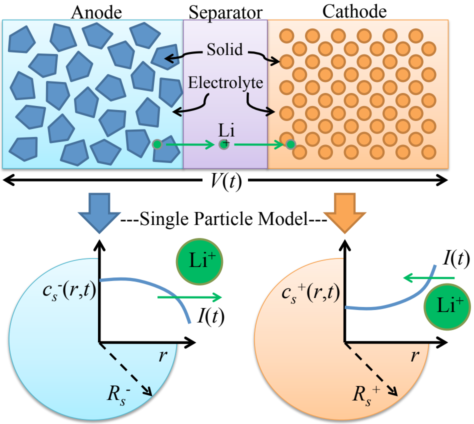
Mathematical Structure

- Two spherical diffusion PDEs
  - States: $c_s^-(r,t)$, $c_s^+(r,t)$



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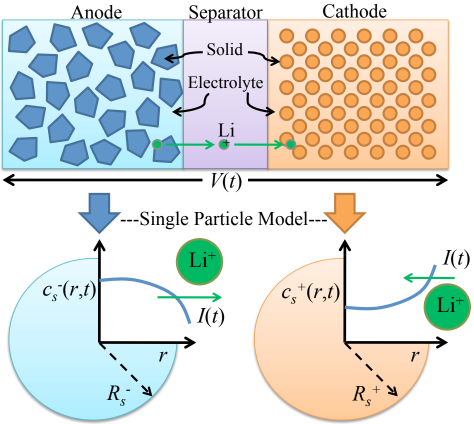

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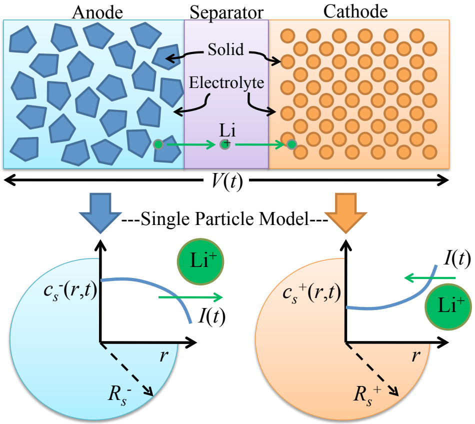
  - Output: $V(t) = h(c_{ss}^-(t), c_{ss}^+(t), I(t))$



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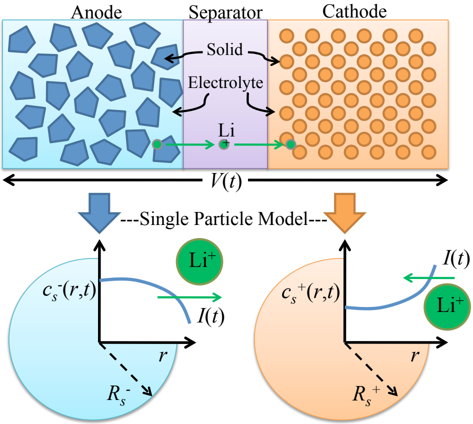

Definitions

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

The SOC Estimation Problem

Problem Statement

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

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Observer Model Equations

$$\frac{\partial c}{\partial t}(r,t) = \varepsilon \frac{\partial^2 c}{\partial r^2}(r,t) \qquad \text{Heat PDE}$$

$$c(0,t) = 0$$

$$\frac{\partial c}{\partial r}(1,t) - c(1,t) = -q\rho I(t)$$

$$\text{Measurement} = c(1,t)$$

Backstepping PDE Estimator

Estimator

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

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\end{aligned}
$$

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

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

The Backstepping Idea

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

Backstepping Transformation

$$
\begin{aligned}
\frac{\partial \tilde{w}}{\partial t}(r,t) &= \varepsilon \frac{\partial^2 \tilde{w}}{\partial r^2}(r,t) + \lambda \tilde{w}(r,t) \\
\tilde{w}(0,t) &= 0 \\
\frac{\partial \tilde{w}}{\partial r}(1,t) &= \frac{1}{2}\tilde{w}(1,t)
\end{aligned}
$$

Exp. Stable Target System

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

Backstepping PDE Estimator

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Kernel PDE

$$
p_{rr}(r,s) - p_{ss}(r,s) = \frac{\lambda}{\varepsilon} p(r,s)
$$

$$
p(0,s) = 0
$$

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

$$
p_1(r) = -p_s(r,1) - \frac{1}{2} p(r,1)
$$

$$
p_{10} = \frac{3 - \lambda/\varepsilon}{2}
$$

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Explicit Solution to Estimator Gains

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

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

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Problem Statement

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

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Relate uncertain parameters to SOH-related concepts

- Capacity fade
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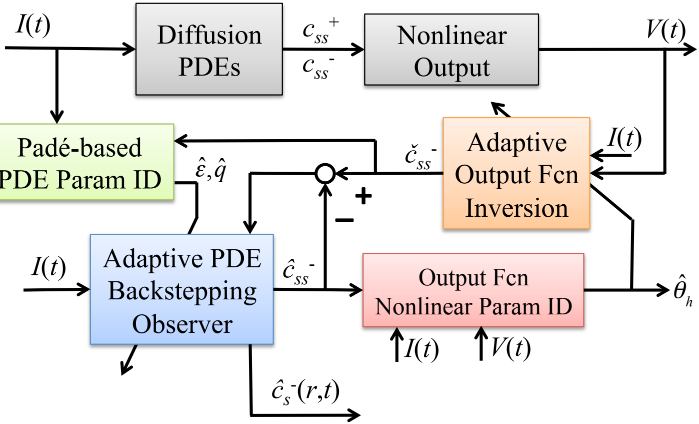
Technical Challenges

- PDE models
- Nonlinear in parameters

Adaptive Observer

Combined State & Parameter Estimation



Padé-based PDE Parameter Identification

PDE Model

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Challenge for adaptive observers:

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Main Idea:

- Approximate PDE transfer function via Padé representation

$$\frac{c_{ss}(s)}{I(s)} = \frac{-q\rho \sinh\left(\sqrt{\frac{s}{\varepsilon}}\right)}{\left(\sqrt{\frac{s}{\varepsilon}}\right)\cosh\left(\sqrt{\frac{s}{\varepsilon}}\right) - \sinh\left(\sqrt{\frac{s}{\varepsilon}}\right)} \approx \frac{-3\rho q\varepsilon^2 - \frac{2}{7}\rho q\varepsilon s}{\varepsilon s + \frac{1}{35}s^2}$$

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Enables the application of standard (e.g. least squares) parameter identification tools applied to vector $\theta_{pde} = [\varepsilon, q\varepsilon, q\varepsilon^2]^T$

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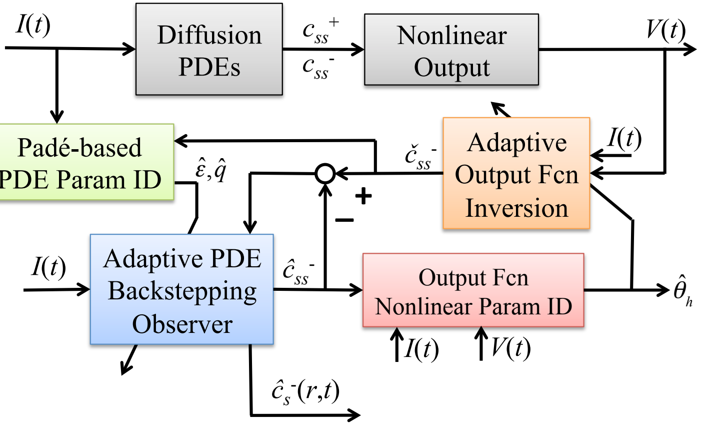

Output Function Nonlinear Parameter ID

Nonlinearly Parameterized Output

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

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Identifiability Analysis Result

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

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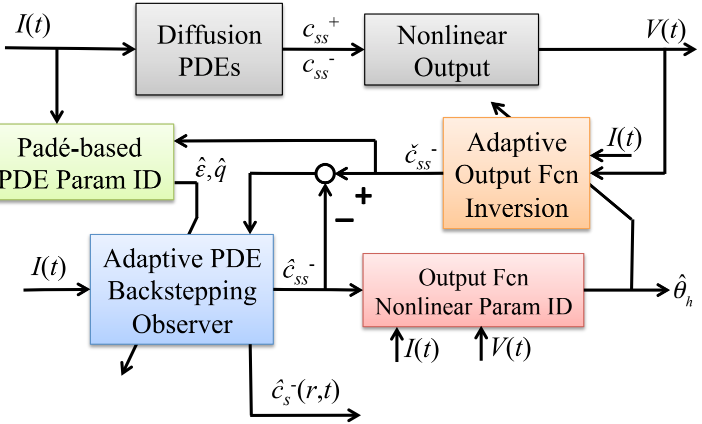

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Recall state observer requires boundary value $c_{ss}^{-}(t)$ for output error injection

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Solve $g(c_{ss}^{-}, t) = 0$ for c_{ss}^{-}, where

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Newton's Method

Main Idea: Construct ODE with exp. stable equilibrium $g(c_{ss}^{-}, t) = 0$

$$\frac{d}{dt}\left[g(\check{c}_{ss}^{-}, t)\right] = -\gamma g(\check{c}_{ss}^{-}, t)$$

which expands to a Newton's method update law:

$$\frac{d}{dt}\check{c}_{ss}^{-} = -\frac{\gamma g(\check{c}_{ss}^{-}, t) + \frac{\partial g}{\partial t}(\check{c}_{ss}^{-}, t)}{\frac{\partial g}{\partial c_{ss}^{-}}(\check{c}_{ss}^{-}, t)}$$

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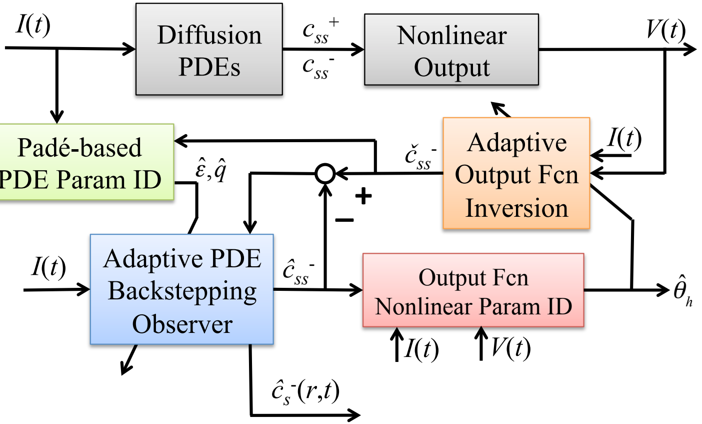
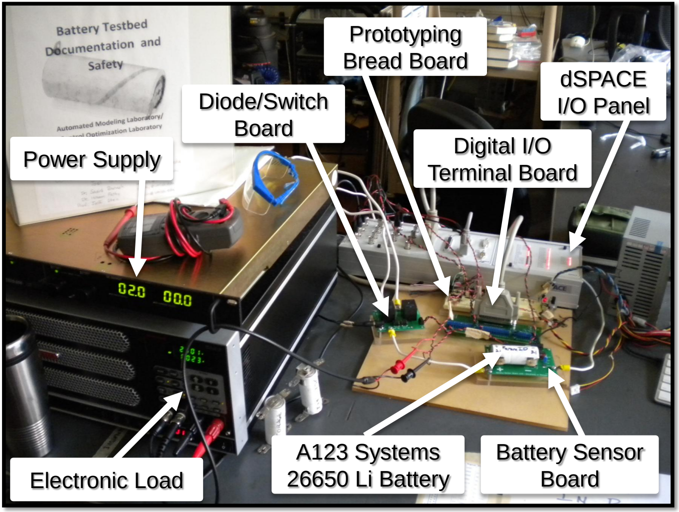
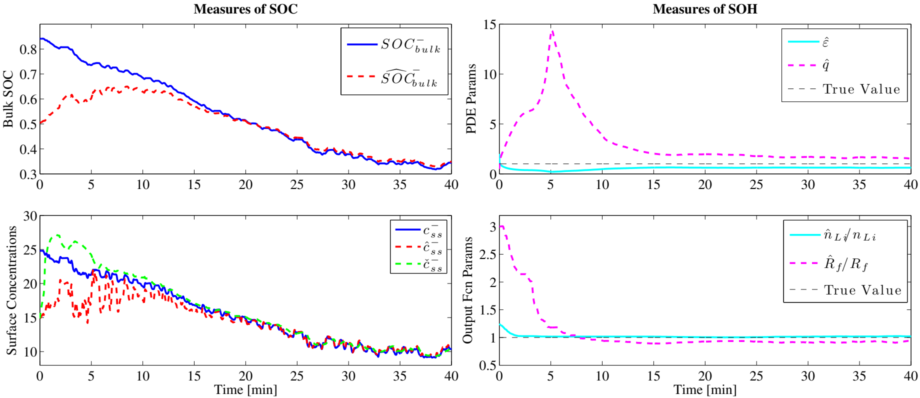


Custom Battery-in-the-Loop Testbed



Results

UDDS Drive Cycle Input



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.

A Short History

- Heuristic algorithms

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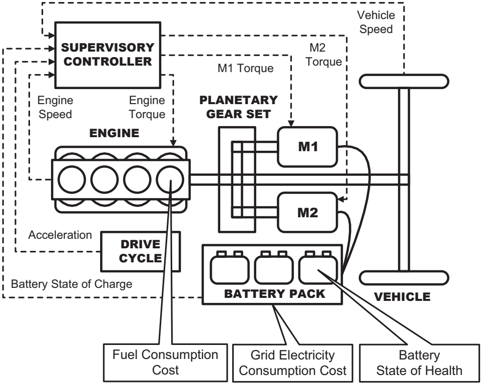
- Moura (2011) - SDP with Electrochemical Battery Model for Health

Power-Split PHEV Model

Ex: Toyota Prius, Ford Escape Hybrid

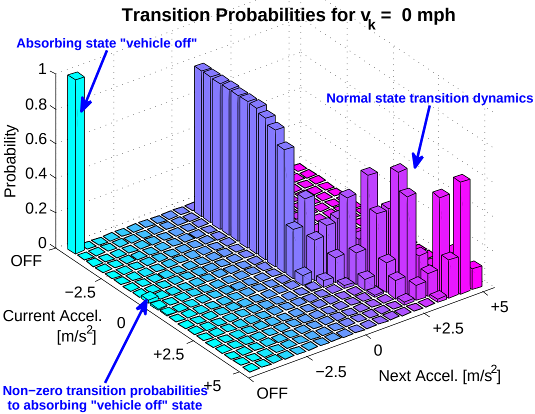
- Control Inputs
  - Engine Torque
  - M1 Torque
- State Variables
  - Engine speed
  - Vehicle speed
  - Battery SOC
  - Vehicle acceleration (Markov Chain)



Markov Chain of Drive Cycle Dynamics

State transition dynamics

$$p_{ijm} = \Pr(a_{k+1} = j | a_k = i, v_k = j)$$



Markov Chain of Drive Cycle Dynamics

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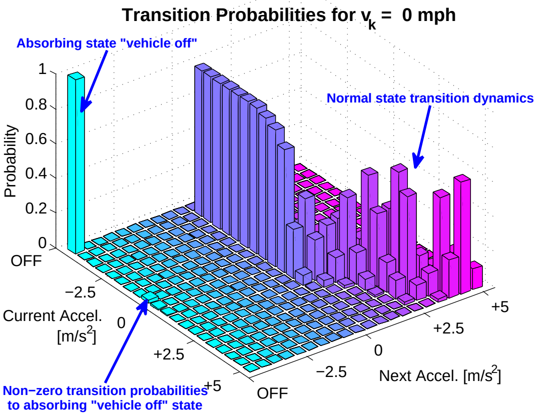

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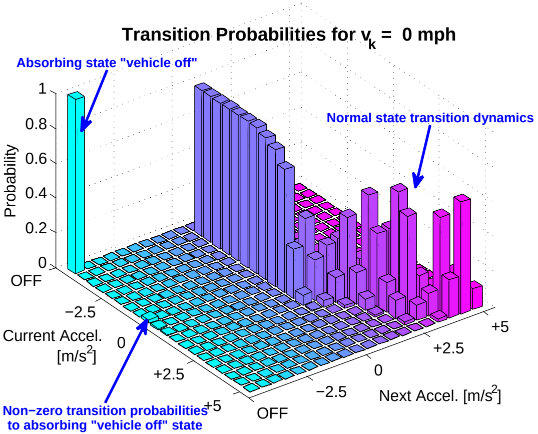

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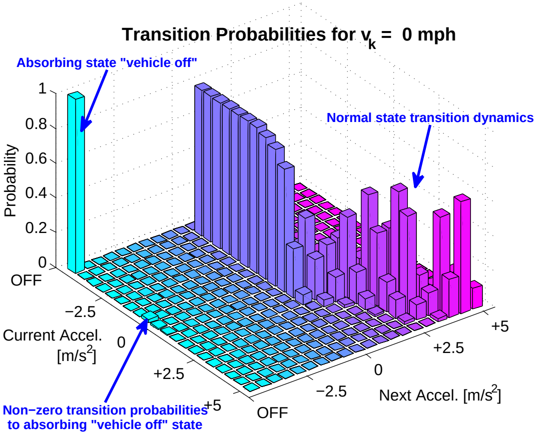


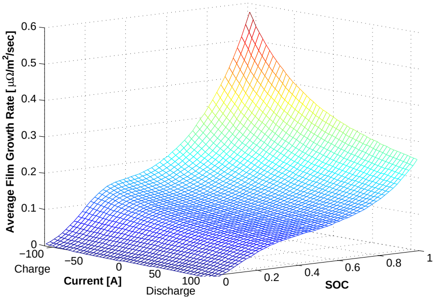
Identification data:

- federal certification cycles, "naturalistic" driving data, 2009 NHTS

Two Battery Health Model Case Studies

Anode-side SEI Layer Growth

- Resistive film layer at solid/electrolyte interface



Ramadass, Haran, White, Popov (2003)

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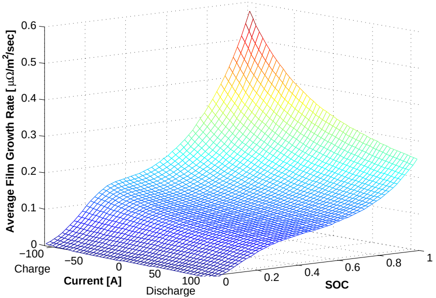
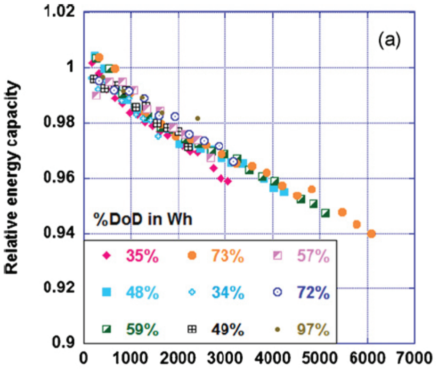


Ramadass, Haran, White, Popov (2003)

Charge Processed

- Capacity fade $\propto$ Ah into/out of cell



Peterson, Apt, Whitacre (2005)

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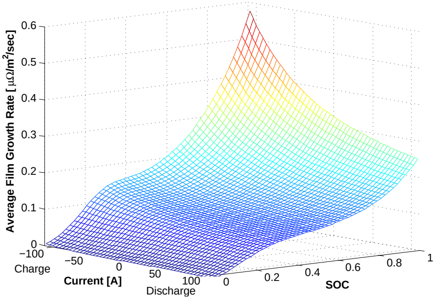

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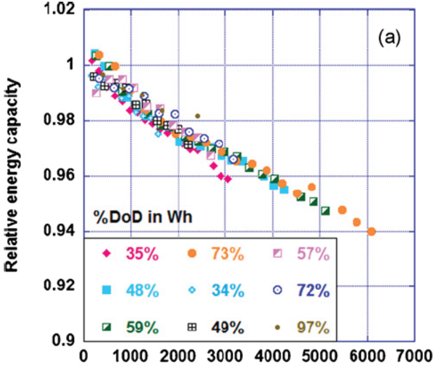

Peterson, Apt, Whitacre (2005)

*Degradation depends on multitude of physical phenomena (e.g. temperature, stress, manufacturing, operating conditions, etc.)

Optimal Control Problem

Multiobjective Shortest-Path Stochastic Dynamic Program

Cost Functional:

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

Constraints:

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

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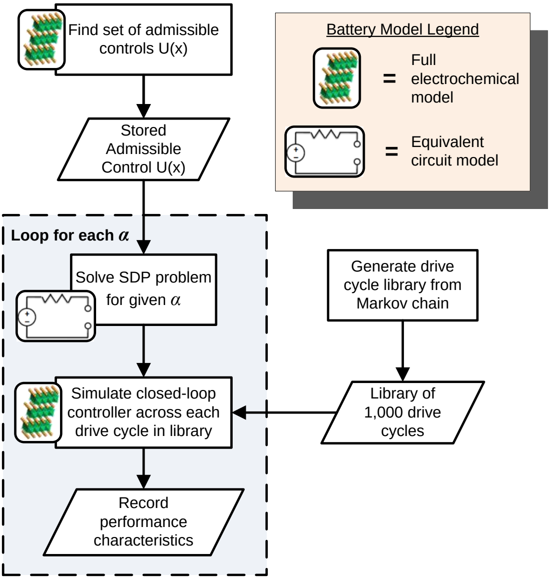
Energy: $c_E(x_k, u_k) = \beta W_{fuel} + \dfrac{-V_{oc} Q_{batt} \dot{SOC}}{\eta_{EVSE}}$

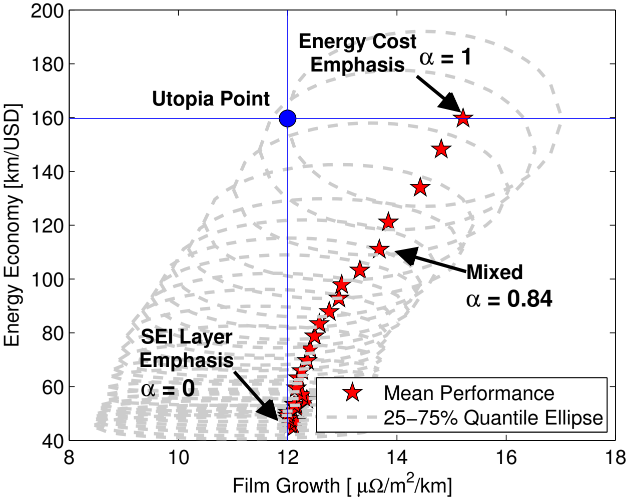
Health: $c_H(x_k, u_k) = \dot{\delta}_{film}(I, SOC)$ OR $|I/I_{max}|$

Optimization Procedure



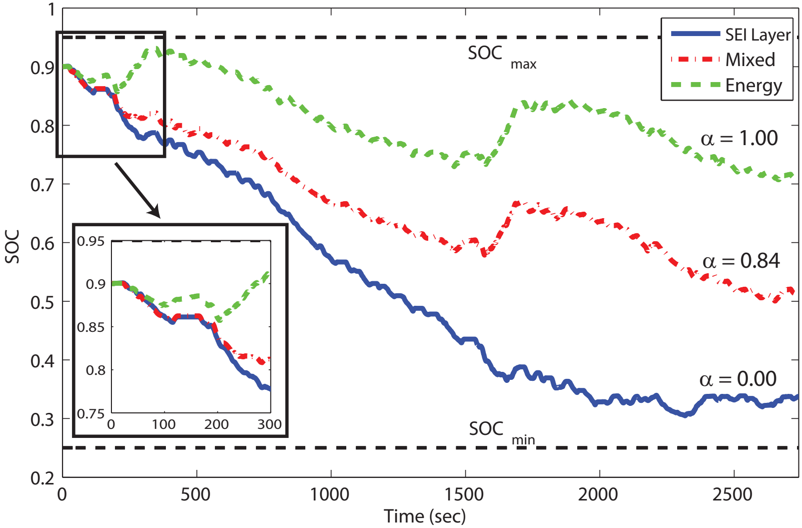
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth



SOC Trajectories

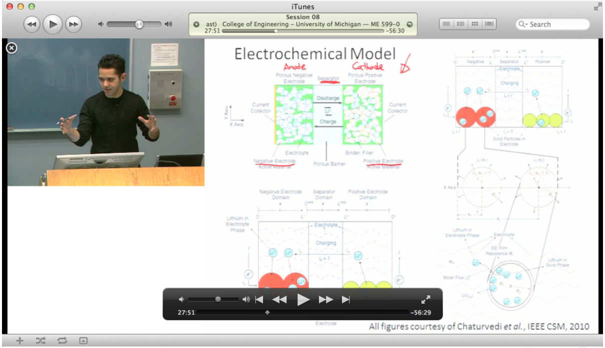
Anode-side SEI Layer Growth | UDDSx2



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



Not Covered Today

- Offline Parameter Identification of Electrochemical Models
  [ACC11, JPS]
- Charge Un-balancing in Battery Packs
  [DSCC09, IEEE TIE]
- Sensor Placement, Estimation, & Control of Battery Pack Thermal Dynamics
  [CDC12]
- Optimal PEV Charging on the Grid
  [DSCC10, JPS]
- Extremum Seeking with Application to Photovoltaic Systems
  [ACC09, IEEE TEC]
- Optimal Boundary Control of PDEs via Weak Variations
  [ACC11, ASME JDSMC]

Summary

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- PHEV power management via electrochemical models and constrained multi-objective stochastic optimal control.

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  - Grid-scale Energy Storage for Renewables & Ancillary Services
- Battery systems and control: A critically important and technically rich research area

Thanks for your attention!
Questions?

Scott J. Moura, Ph.D.
UC Presidential Postdoctoral Fellow
UC San Diego
http://flyingv.ucsd.edu/smoura/