Adaptive Estimation and Control of Models for Battery Electrochemistry

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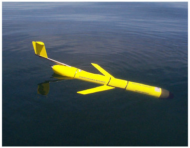
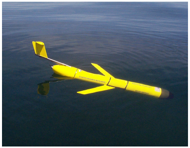
A Golden Era


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

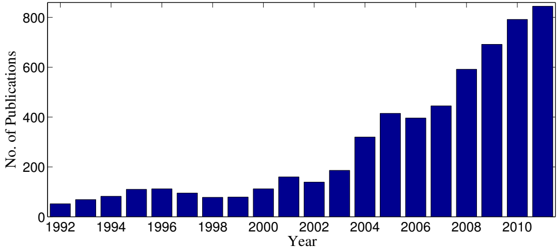



A123 SYSTEMS
2MW H-APU
HYBRID ANCILLARY POWER UNIT

A Golden Era

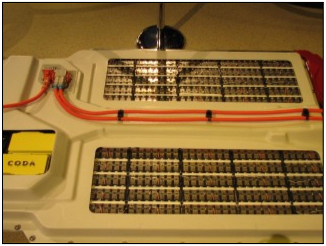


Keyword: “Battery Systems and Control”



Battery Management Systems

- Modeling & Identification
- SOC/SOH Estimation
- Constrained Control
- ...



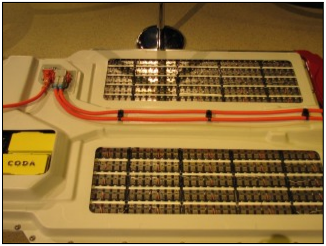
Open Problems in Energy Storage and Control

Battery Management Systems

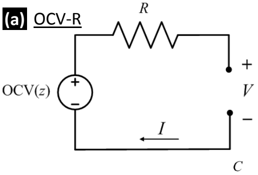
- Modeling & Identification
- SOC/SOH Estimation
- Constrained Control
- ...

Energy Storage in Smart Grid

- Modeling & Design
- Hierarchical Control Framework
- Renewables
- ...

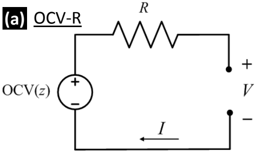


Equivalent Circuit Model

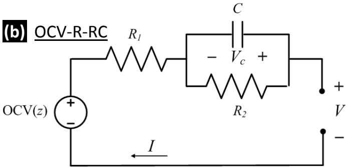


Equivalent Circuit Model

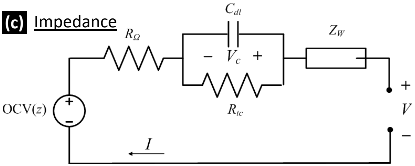
(a) OCV-R



(b) OCV-R-RC



(c) Impedance



Battery Models

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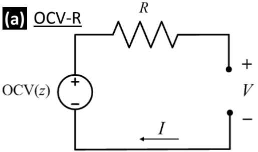

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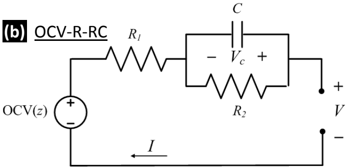

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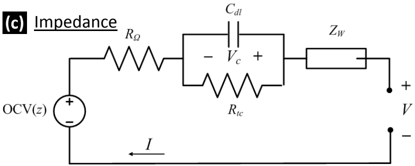
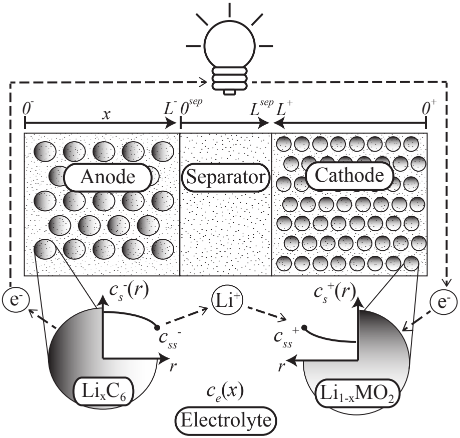
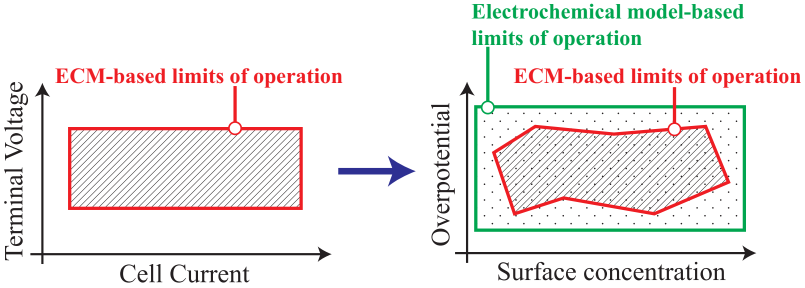


Electrochemical Model



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

Outline

Outline

A Short History

- Equivalent Circuit Model

- Electrochemical Model

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  - 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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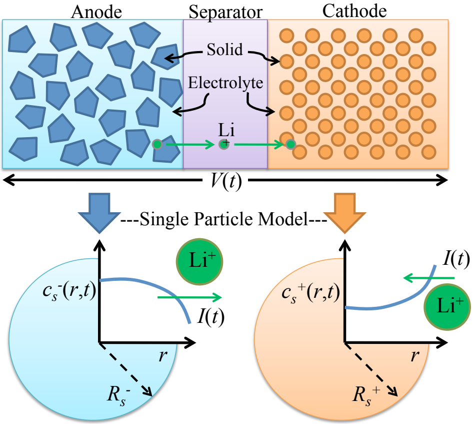
  - S. Moura (2012) - Adaptive PDE Observer on SPM (States <u>& Params</u>)

Single Particle Model (SPM)

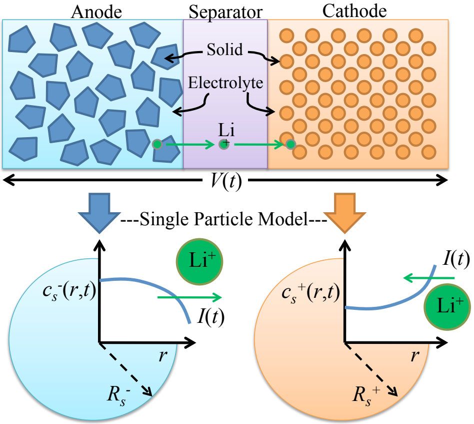


Single Particle Model (SPM)

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:

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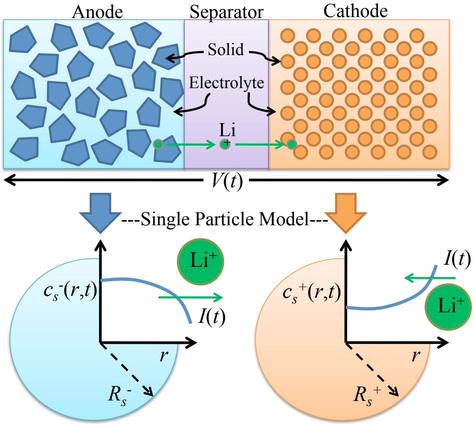

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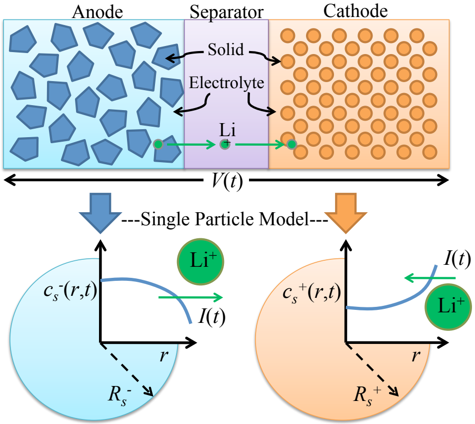
Voltage Output Function:

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



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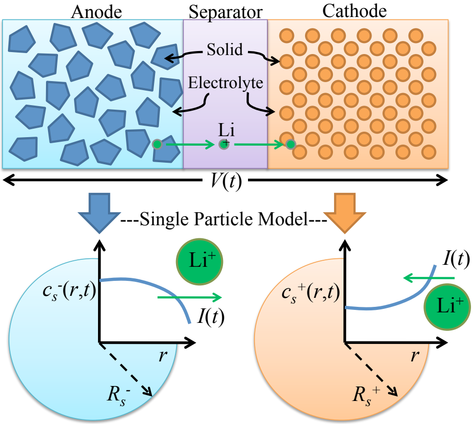

Definitions

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

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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Simplify the Math

- Model reduction to achieve observability
- Normalize time and space
- State transformation

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Observer Model Equations

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

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

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

$$\text{Measurement} = c(1,t) = \check{c}_{ss}^-(t)$$

Backstepping PDE Estimator

Estimator

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

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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Relate uncertain parameters to SOH-related concepts

- Capacity fade
- Power fade

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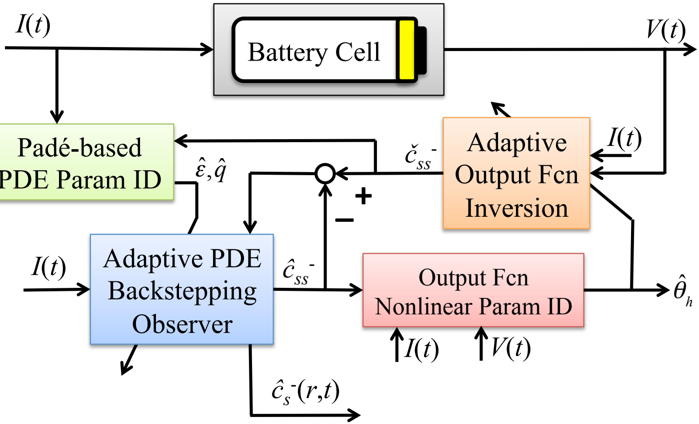
Technical Challenges

- PDE models
- Nonlinear in parameters

Adaptive Observer

Combined State & Parameter Estimation



Padé-based PDE Parameter Identification

PDE Model

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

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Challenge for adaptive observers:

- Cannot re-express model such that ε multiplies measured signals

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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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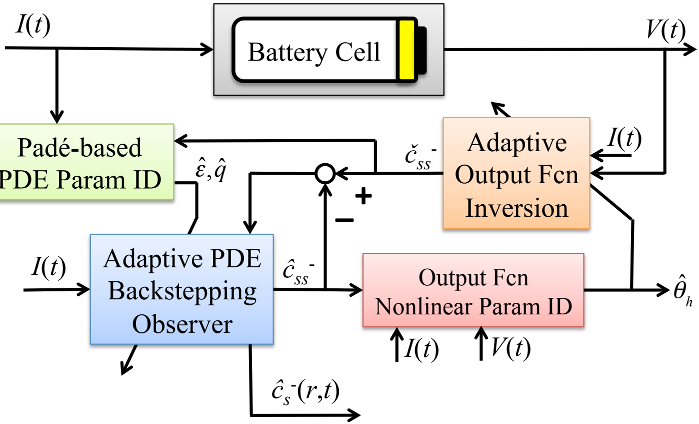

Output Function Nonlinear Parameter ID

Nonlinearly Parameterized Output

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

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- Linear dependence between parameters?

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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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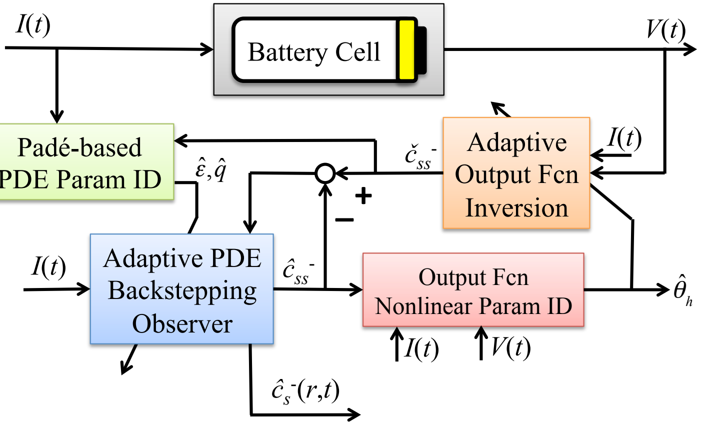

Adaptive Output Function Inversion

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

Adaptive Output Function Inversion

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

Nonlinear Function Inversion

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

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

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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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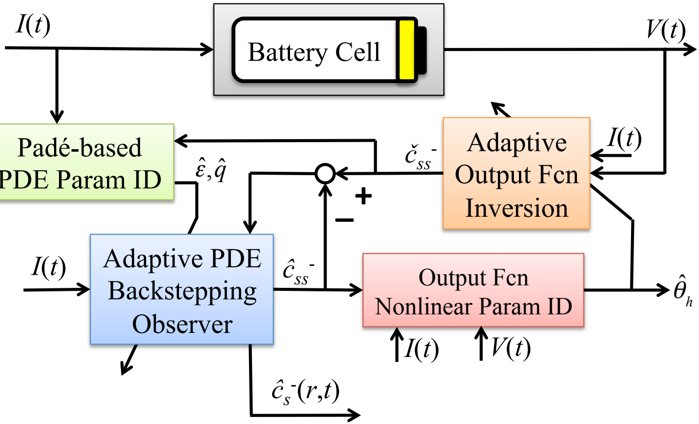
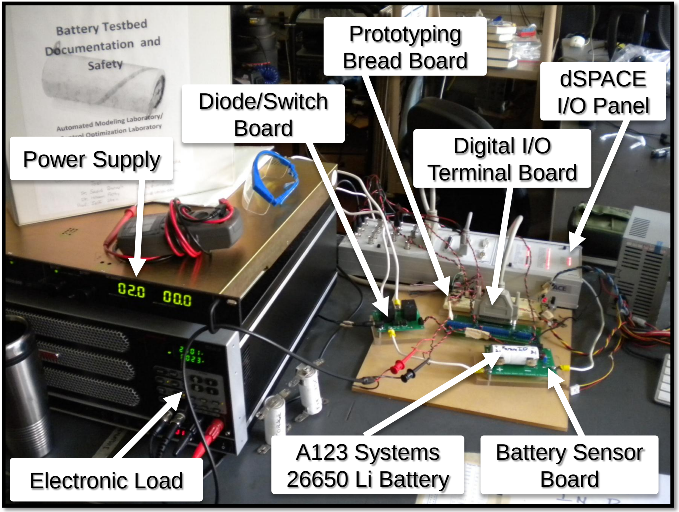
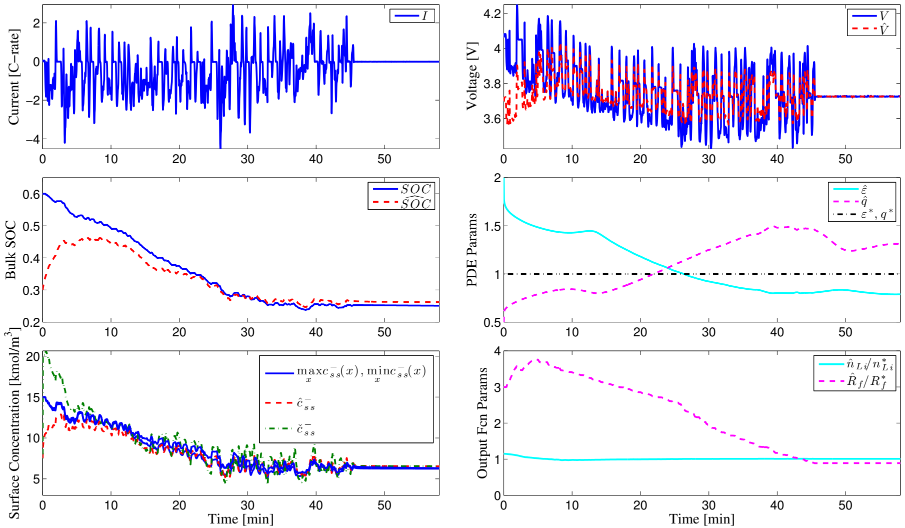


Custom-Built Battery-in-the-Loop Testbed



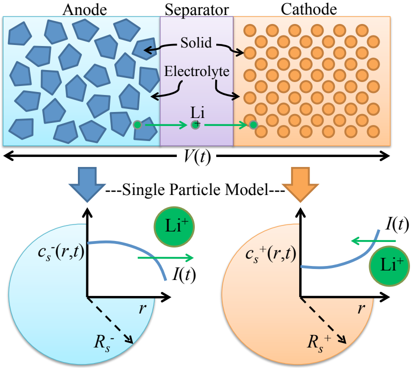
Results

UDDS Drive Cycle Input

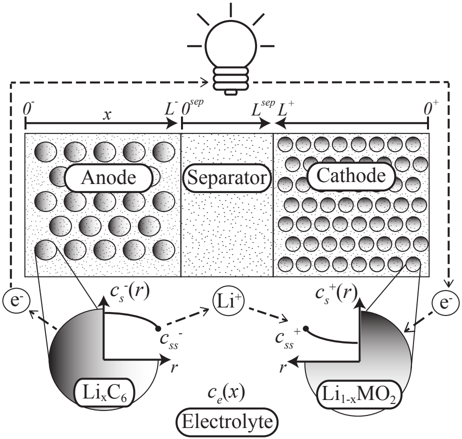


Estimator with Electrolyte Dynamics

Single Particle Model



Full Model w/ electrolyte



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Operate Batteries at their Physical Limits

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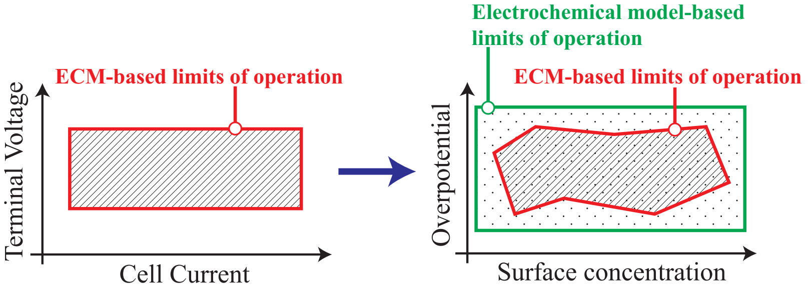
Problem Statement

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

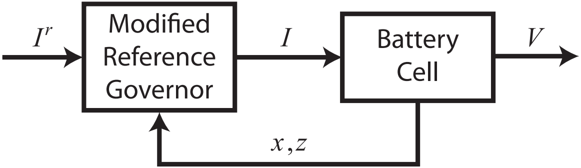


Constraints

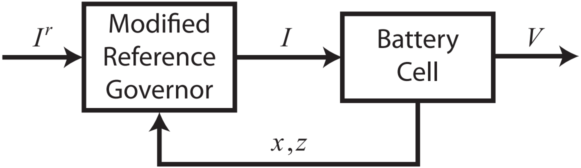
Variable	Definition	Constraint
$I(t)$	Current	Power electronics limits
$c_s^{\pm}(x,r,t)$	Li concentration in solid	Saturation/depletion
$\frac{\partial c_s^{\pm}}{\partial r}(x,r,t)$	Li concentration gradient	Diffusion-induced stress
$c_e(x,t)$	Li concentration in electrolyte	Saturation/depletion
$T(t)$	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)



The Algorithm: Modified Reference Governor (MRG)

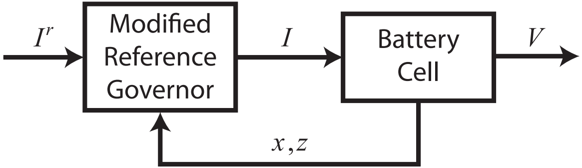


MRG Equations

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

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

The Algorithm: Modified Reference Governor (MRG)



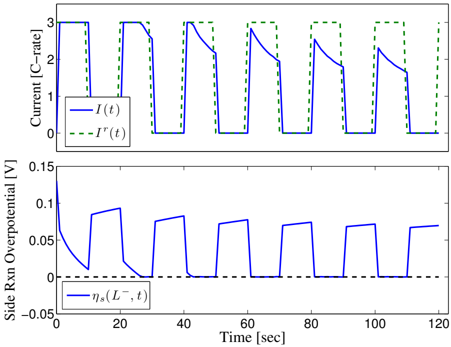
MRG Equations

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

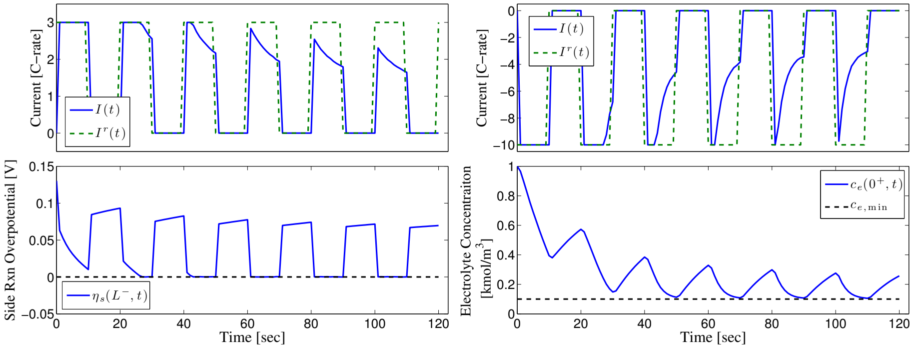
Def'n: Admissible Set $\mathcal{O}$

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

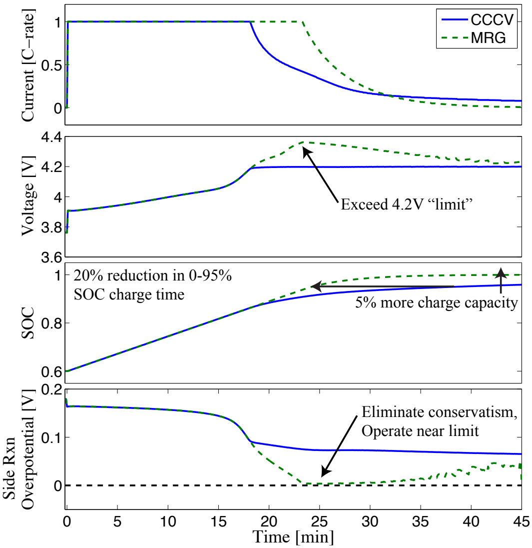
Simulations: Operate at the Limits



Simulations: Operate at the Limits



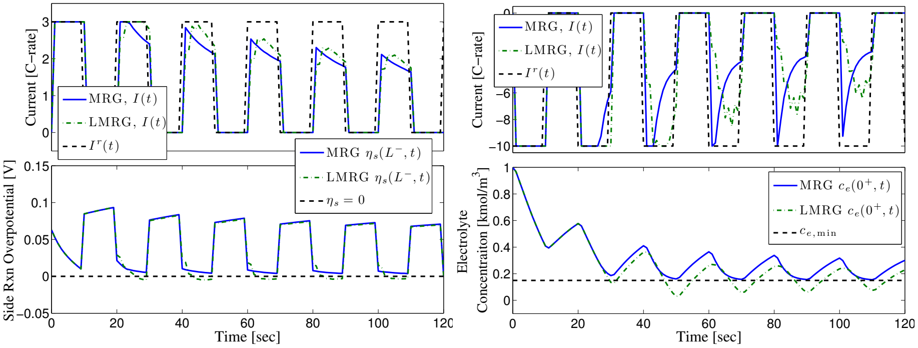
Application to Charging



Linear Reference Governor

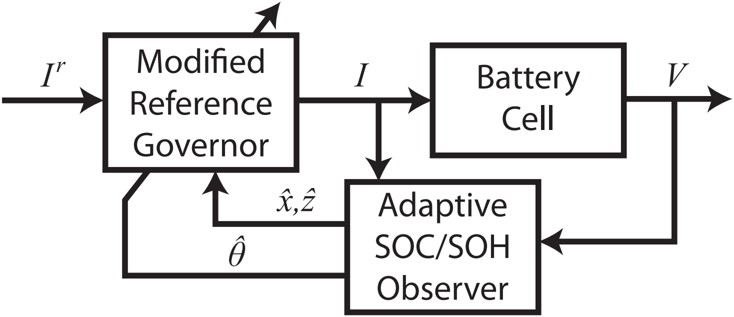
Modified Reference Governor (MRG) : Simulations

Linearized MRG (LMRG) : Explicit function evaluation



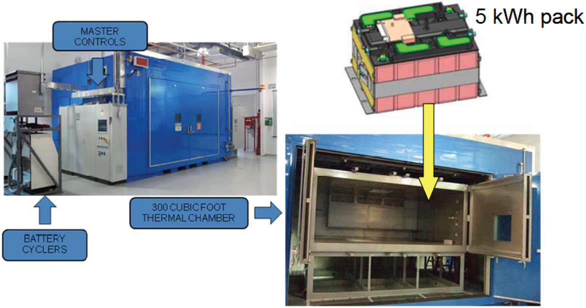
Reference Governor + Adaptive Observer

Simultaneous Estimation and Control!



Upcoming Experimental Research

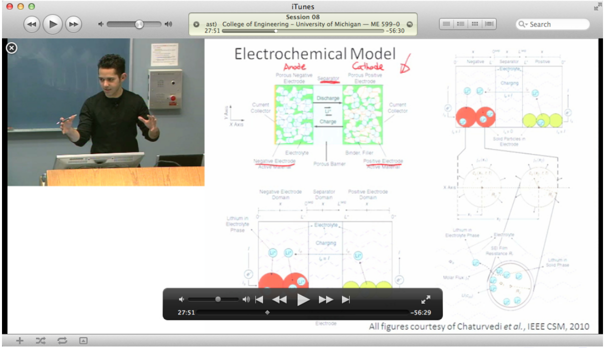
In Collaboration with Bosch, Cobasys, and ARPA-E



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



Outline

PHEV Power Management

Problem Statement

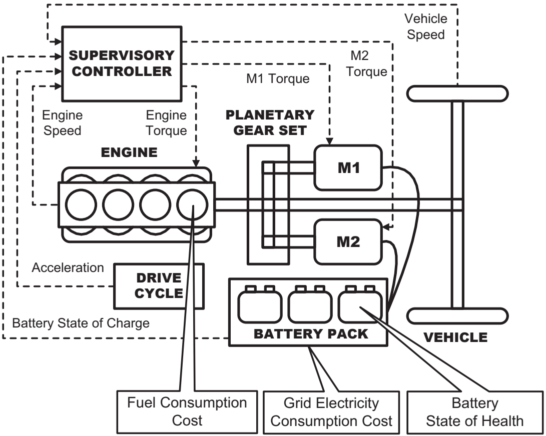
Design a supervisory control algorithm for plug-in hybrid electric vehicles (PHEVs) that splits engine and battery power in some optimal sense.

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

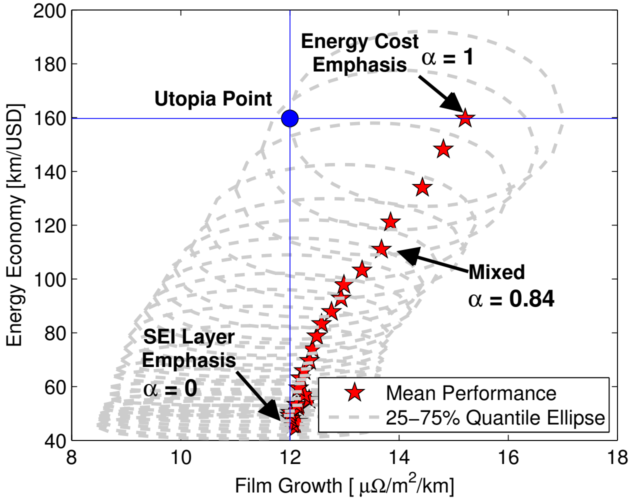
- Control Inputs
  - Engine Torque
  - M1 Torque
- State Variables
  - Engine speed
  - Vehicle speed
  - Battery SOC
  - Vehicle acceleration (Markov Chain)



Control Optimization: Minimize energy consumption cost AND battery aging

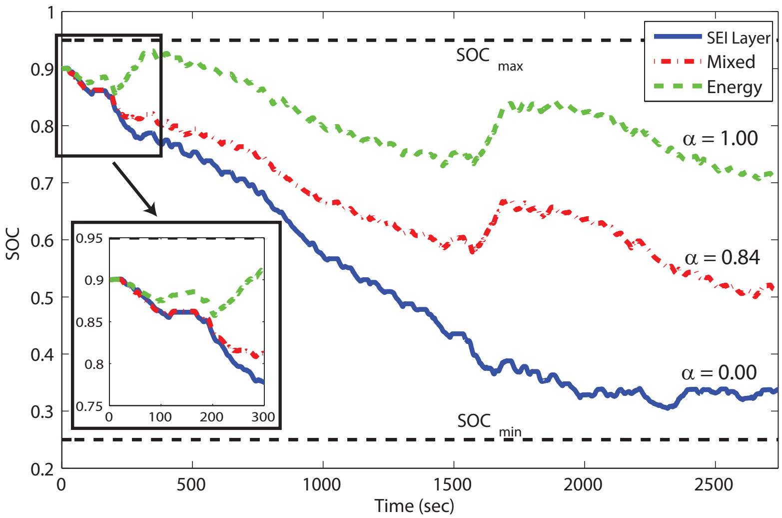
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth

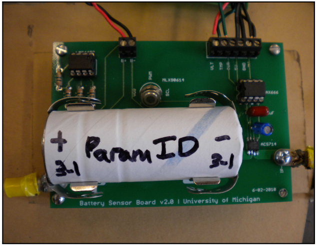


SOC Trajectories

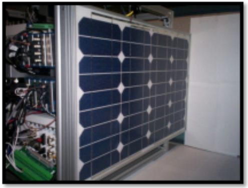
Anode-side SEI Layer Growth | UDDSx2



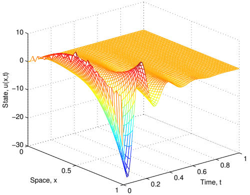
Energy & Controls Research: More than batteries



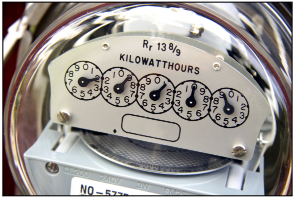
- SOC/SOH Estimation
- Constrained Control
- Model ID from Experimental Data
- Battery Pack Unbalancing
- PHEV Power Management



Control of Photovoltaic Systems



Optimal Control Theory for Distributed Parameter Systems



Demand Response in Smart Grids

Outline

Summary

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.

Control Theory + Electrochemical Battery Models:
A critically important and fundamentally rich research area

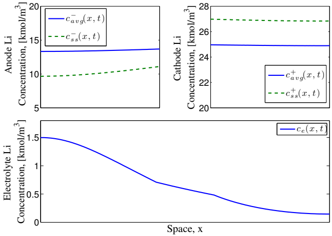
Thanks for your attention!
Questions?

Scott Moura, Ph.D.
http://flyingv.ucsd.edu/smoura/

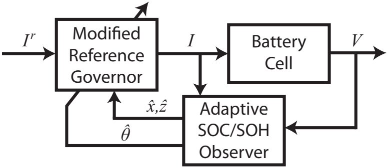
Advanced Battery Management Systems

ARPA-E

State Estimation w/ Electrolyte



Estimator + Reference Governor



Optimal charge/discharge

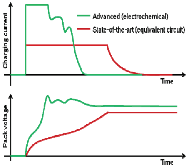


Figure 2: Charging phase of each duty cycle for BMS validation

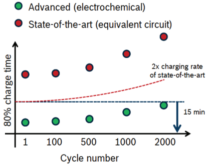
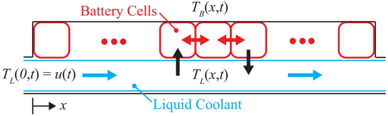


Figure 3: Comparison of charging time on a cycle to cycle basis for conventional BMS and advanced BMS

Thermal Management



Optimal Control of Distributed Parameter Systems

Models

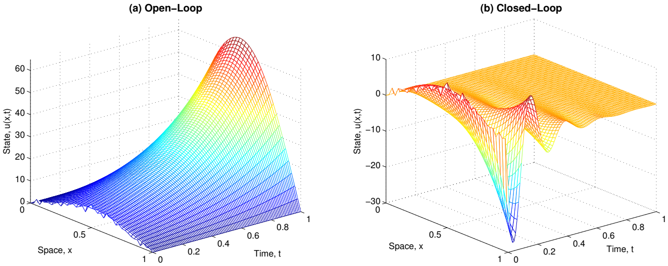
- Diffusion-Reaction-Advection
- Transport, Delays
- Waves, Beams, Nonlinear
- ...

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