Control & Estimation of Electrochemical Model-based Battery Management Systems

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Cymer Center for Control Systems and Dynamics
Mechanical & Aerospace Engineering
UC San Diego

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Robert Bosch LLC
Research and Technology Center
Palo Alto, CA

Outline

1. About Me
2. PHEV Power Management
   - Models
   - Stochastic Optimal Control
   - Sample Results
3. SOC/SOH Estimation
   - Single Particle Model
   - State Estimation via PDE Backstepping
   - Parameter Identification via Adaptive & Nonlinear Control
4. Outlook on Collaborative Efforts with Bosch

About Me: Education & Work Experience

Education

- Postdoctoral Fellow - UC San Diego (July 2011 - June 2013)
- Ph.D. & M.S.E. - University of Michigan (Sept 2006 - Apr 2011)
- B.S. - UC Berkeley (Aug 2002 - June 2006)

all in Mechanical Engineering

Industrial Work Experience

- DaimlerChrysler Corp - Electrical Engineering (June 2006 - Aug 2006)
- Ford Motor Company - Manufacturing (June 2005 - Aug 2005)
- Southern California Edison - Staff Engineering (June 2004 - Aug 2004)

About Me: Publications

Authored 20 peer-reviewed publications in energy systems and control

- 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]

About Me: Honors

- UC Presidential Postdoctoral Fellowship
- NSF Graduate Student Fellowship
- University of Michigan Distinguished Dissertation Honorable Mention
- University of Michigan Distinguished Leadership Award
- Best Student Paper Finalist
  - 2011 American Control Conference
  - 2009 ASME Dynamic Systems and Control Conference
- SHPE Conference Best Paper Award

Open Problems in Battery Systems and Control

Cell Level

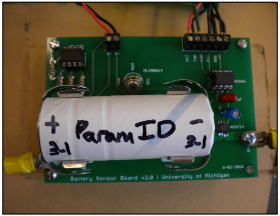
- Modeling & Design
- Optimal Control under Constraints
- SOC/SOH Estimation
- ...

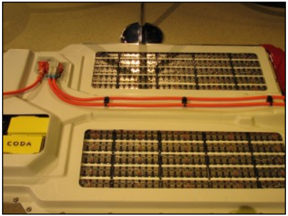
Pack Level

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

Smart-Grid Level

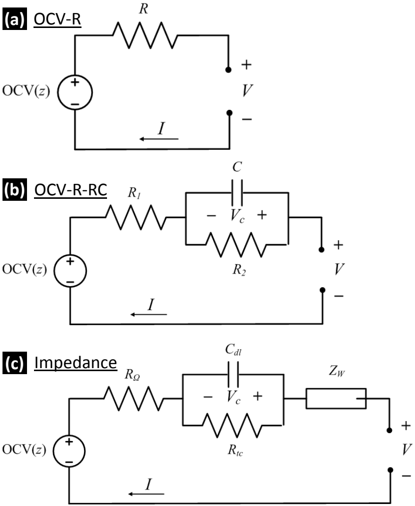
- Renewable Energy Integration
- Optimal Power Flow
- PEV Power Management
- ...



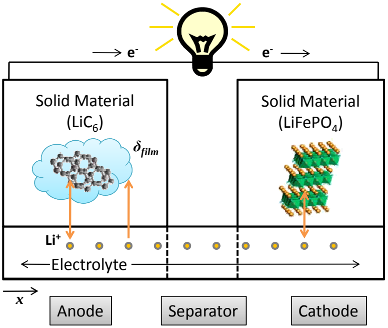


Battery Models

Equivalent Circuit Model



Electrochemical Model



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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

A Short History

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- Rizzoni (2004) - Equivalent Consumption Minimization Strategy
- Peng & Grizzle (2004) - Deterministic Dynamic Programming
- Peng & Grizzle (2007) - Stochastic Dynamic Programming
- Bemporad / Vahidi / Kolmanovsky (2010) - Model Predictive Control

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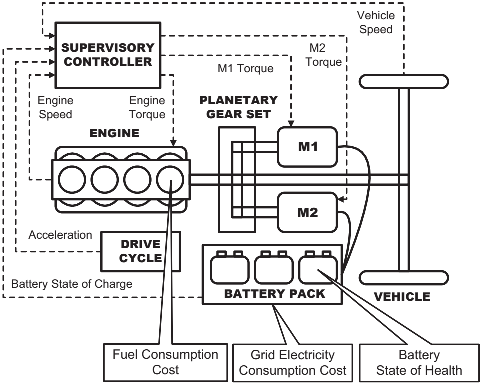
- Moura (2011) - SDP with Electrochemical Battery Model for Health

Power-Split PHEV Model

Ex: Toyota Prius, Ford Escape Hybrid

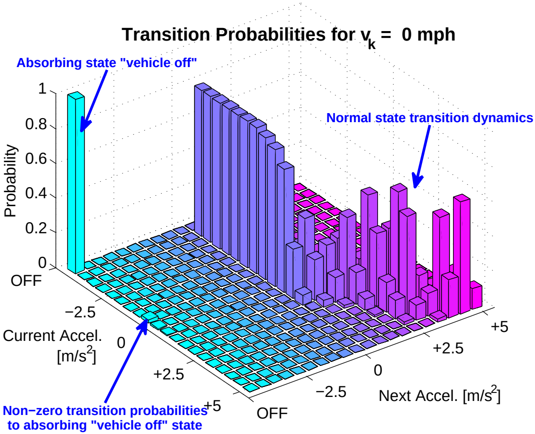
- Control Inputs
  - Engine Torque
  - M1 Torque
- State Variables
  - Engine speed
  - Vehicle speed
  - Battery SOC
  - Vehicle acceleration (Markov Chain)



Markov Chain of Drive Cycle Dynamics

State transition dynamics

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



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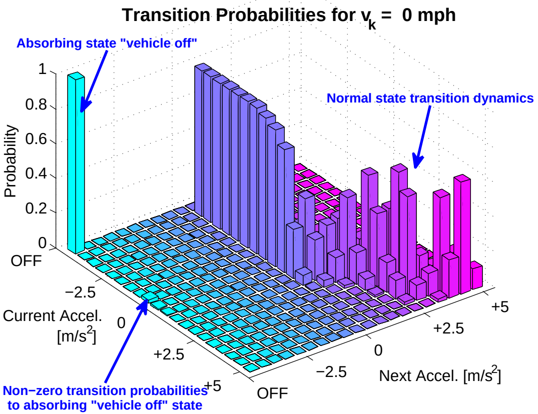

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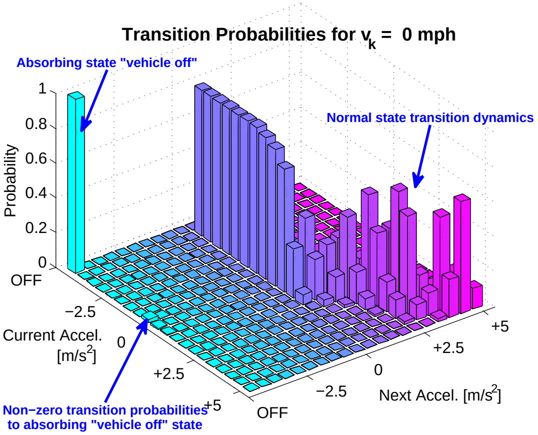
Absorbing state "vehicle off"

$$1 = \Pr(a_{k+1} = t | a_k = t, v_k = 0)$$



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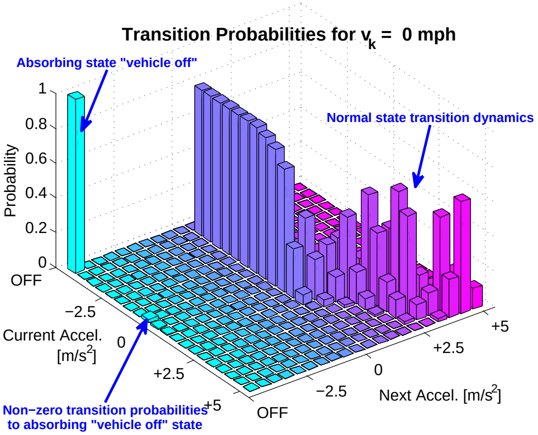


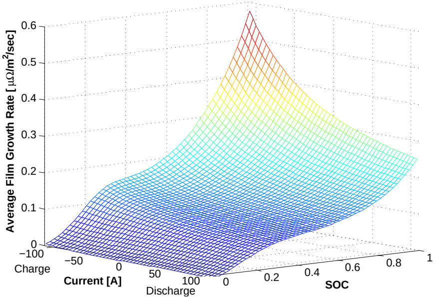
Identification data:

- 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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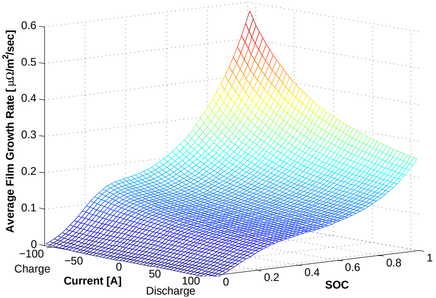

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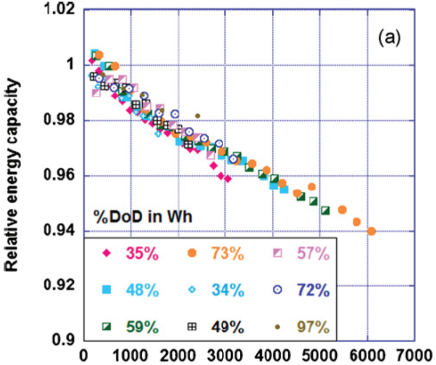
Charge Processed

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



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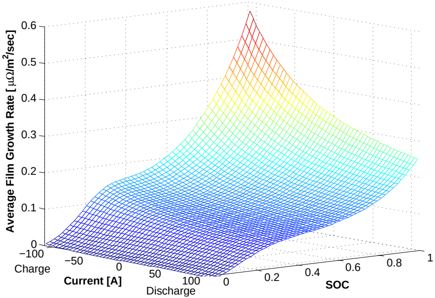

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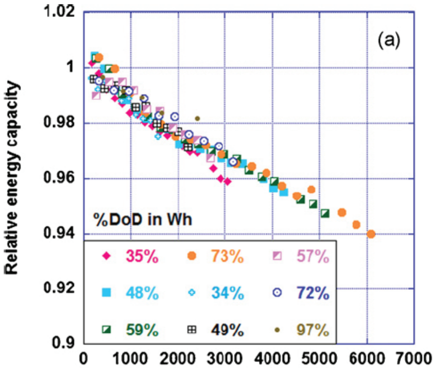

Peterson, Apt, Whitacre (2005)

*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:

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

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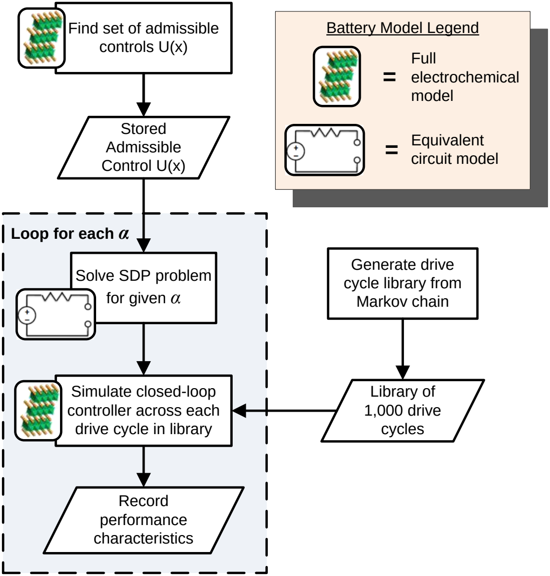
Energy: $c_E(x_k, u_k) = \beta W_{fuel} + \dfrac{-V_{oc} Q_{batt} \dot{SOC}}{\eta_{EVSE}}$

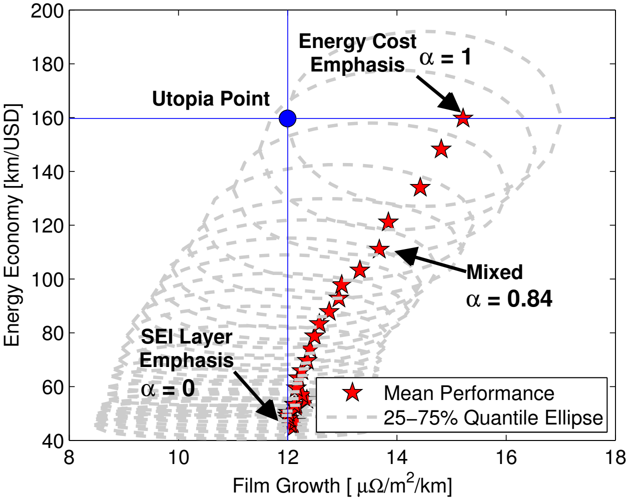
Health: $c_H(x_k, u_k) = \dot{\delta}_{film}(I, SOC)$ OR $|I/I_{max}|$

Optimization Procedure



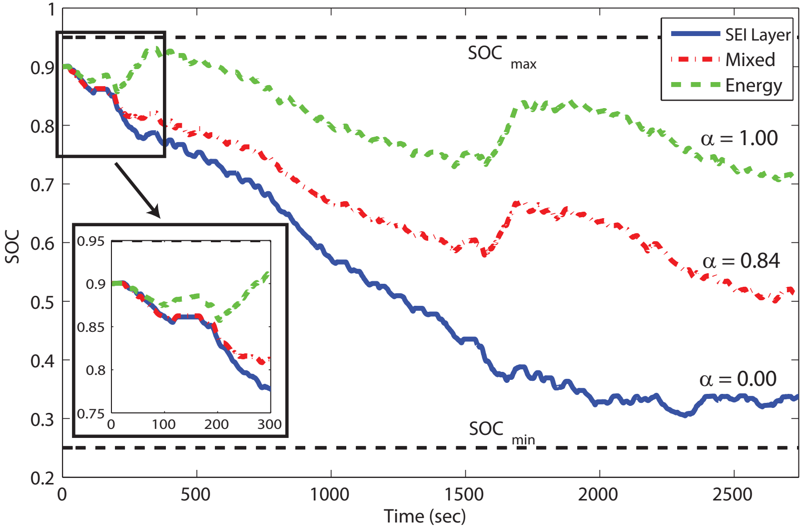
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth



SOC Trajectories

Anode-side SEI Layer Growth | UDDSx2

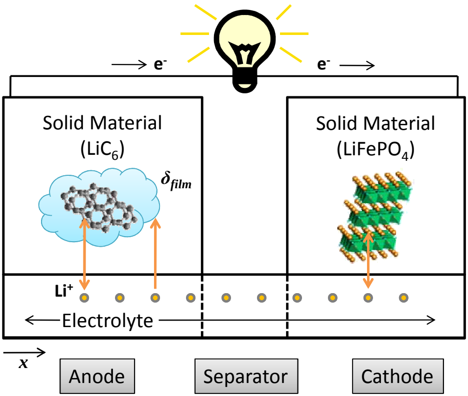


Outline

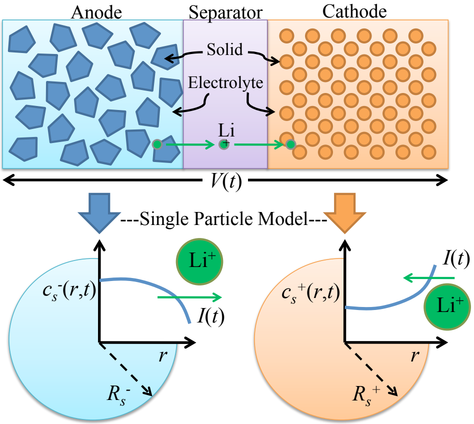
SOC/SOH Estimation

Problem Statement

Simultaneously estimate SOC (states) and SOH (parameters) via an electrochemical model with measurements of voltage and current, only.

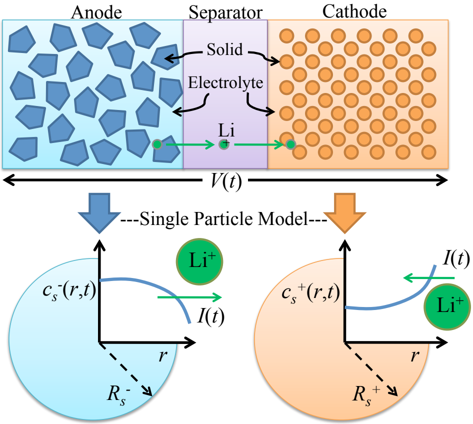


Single Particle Model (SPM)



Mathematical Structure

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



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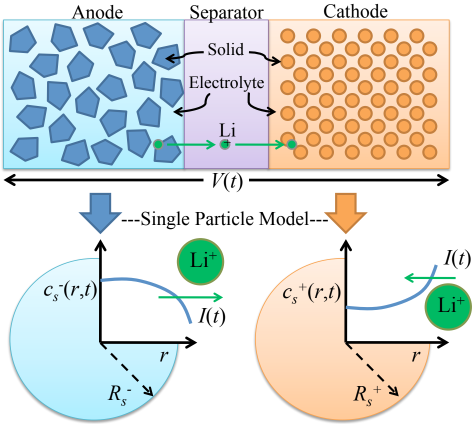
  - Input: $I(t)$



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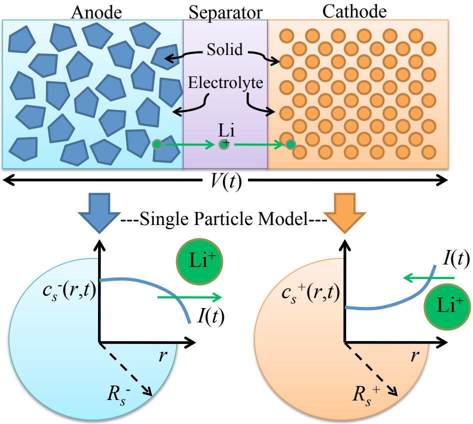
  - Input: $I(t)$
- Nonlinear output function of PDEs' boundary values
  - Output: $V(t) = h(c_{ss}^-(t), c_{ss}^+(t), I(t))$



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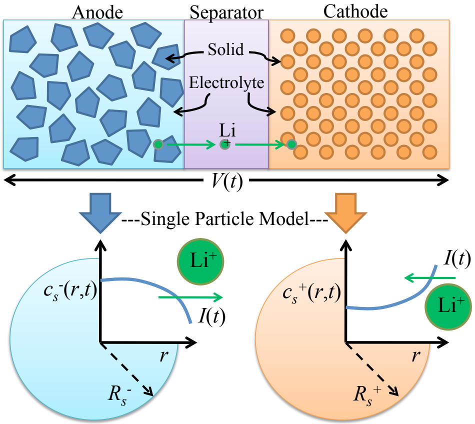

Definitions

- 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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Simplify the Math

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

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Observer Model Equations

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

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

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

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

Backstepping PDE Estimator

Estimator

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

- Form error system $\tilde{c}(r,t)$
- Select target system $\tilde{w}(r,t)$ exponentially stable
- Find backstepping transformation: $\tilde{c}(r,t) \to \tilde{w}(r,t)$
- Derive kernels for transformation and solve analytically

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

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

The SOH Estimation Problem

Problem Statement

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

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Relate uncertain parameters to SOH-related concepts

- Capacity fade
- Power fade

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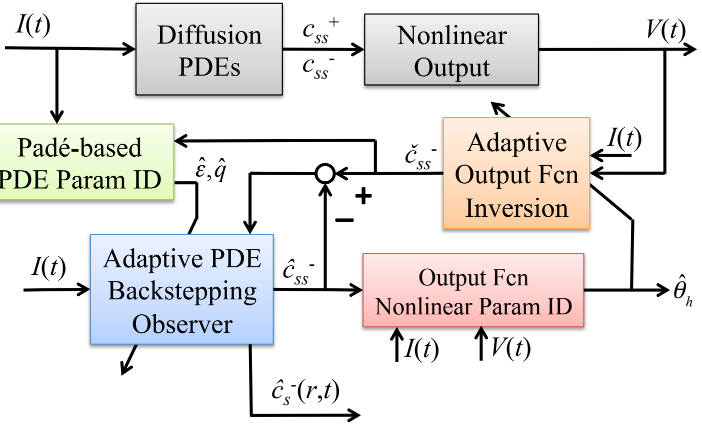
Technical Challenges

- PDE models
- Nonlinear in parameters

Adaptive Observer

Combined State & Parameter Estimation



Output Function Nonlinear Parameter ID

Nonlinearly Parameterized Output

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

- θ contains many parameters
- 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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Enables the application of nonlinear least squares parameter identification tools applied to vector θ_h

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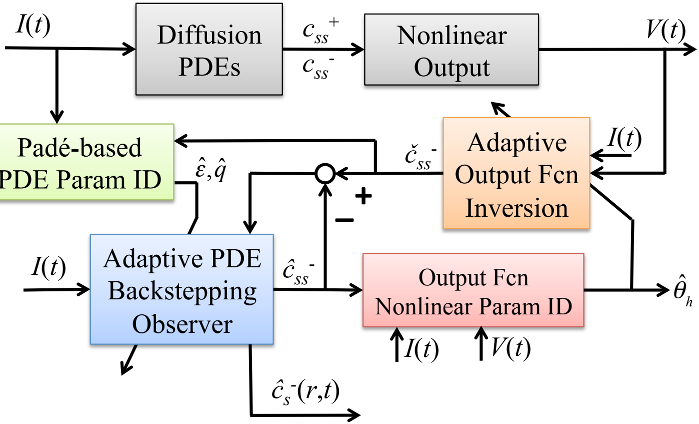
Combined State & Parameter Estimation



Adaptive Output Function Inversion

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

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Nonlinear Function Inversion

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

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

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

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

Newton's Method

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

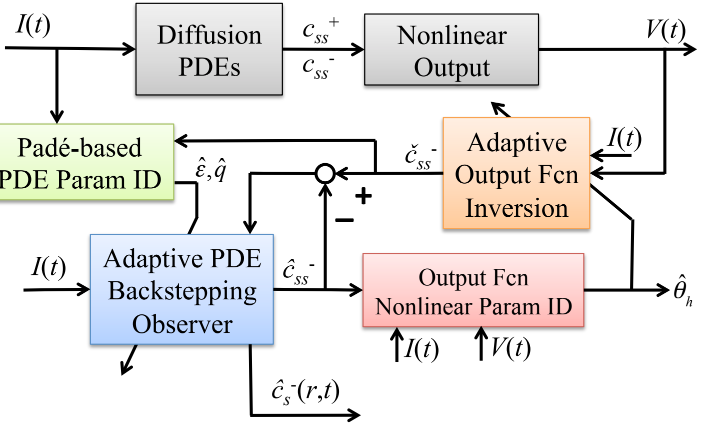
$$\frac{d}{dt}\left[g(\check{c}_{ss}^-, t)\right] = -\gamma g(\check{c}_{ss}^-, t)$$

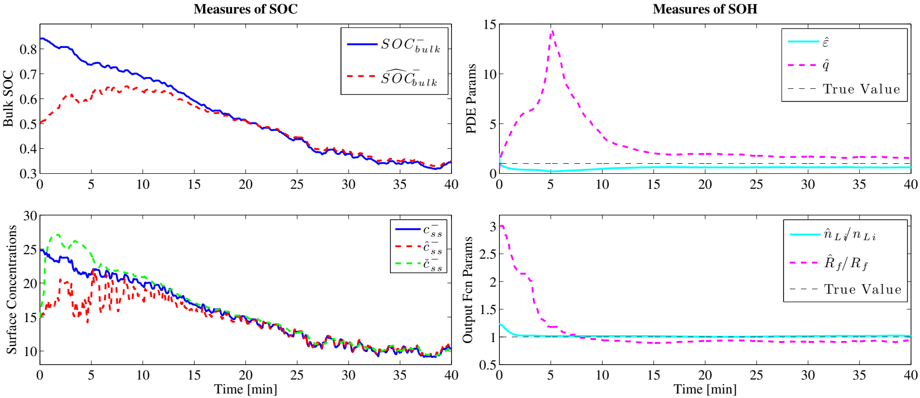
which expands to a Newton's method update law:

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

Adaptive Observer

Combined State & Parameter Estimation

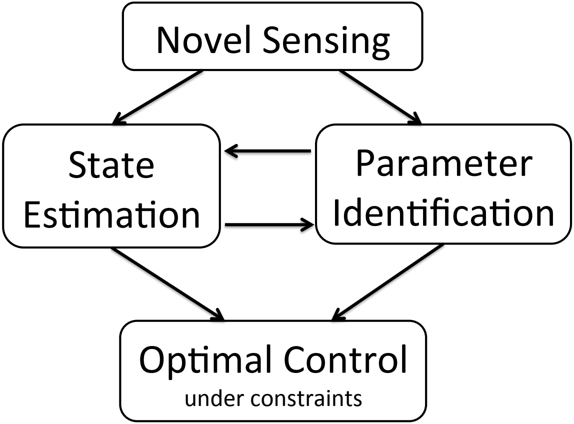




Work in Progress: Validation on Full Electrochemical Model

Outline

Vision for Electrochemical-model based BMS



Future Research Tasks

Adaptive SOC/SOH Observer for Single Particle Model

- Simulator for full model
- Validate adaptive observer
- Publish

Target completion: May 15

Parameter Estimation for Full Model (i.e. retain x-dimension)

- Analyze parameter identifiability
- Develop parameter estimation algorithm
- Validation
- Publish

Target completion: Aug 1

ARPA-E AMPED Project

ARPA-E AMPED Project

Advanced Management and Protection of Energy-storage Devices

A Coupled Mechanical/Electrochemical Approach

- Stress/strain sensor in case
- Analyze observability and parameter identifiability
- Estimate SOC, stress, and params

Optimal-Safe Fast Charging - A Model Predictive Control Approach

- Output feedback
- Temp, side-rxn, and stress constraints

Thanks for your attention!
Questions?

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

Nonlinear Identifiability Analysis

Parameterized Output

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

$$\theta = \left[n_{Li}, \frac{1}{a^+ A L^+ k^+ \sqrt{c_e^0}}, \frac{1}{a^- A L^- k^- \sqrt{c_e^0}}, R_f \right]^T$$

Linear dependence between parameters?

Parameter Sensitivity

$$S_i = \frac{\partial h}{\partial \theta_i}$$

$$S = [S_1, S_2, S_3, S_4]^T \qquad S \in R^{n_T \times 4}$$

A particular decomposition of $S^T S$ reveals linear dependence between parameters!

Nonlinear Identifiability Analysis

Decomposition of $S^T S = D^T C D$

$$D = \text{diag}(\|S_1\|, \|S_2\|, \|S_3\|, \|S_4\|)$$

$$C = \begin{bmatrix} 1 & \frac{\langle S_1, S_2 \rangle}{\|S_1\|\|S_2\|} & \frac{\langle S_1, S_3 \rangle}{\|S_1\|\|S_3\|} & \frac{\langle S_1, S_4 \rangle}{\|S_1\|\|S_4\|} \\ \frac{\langle S_2, S_1 \rangle}{\|S_2\|\|S_1\|} & 1 & \frac{\langle S_2, S_3 \rangle}{\|S_2\|\|S_3\|} & \frac{\langle S_2, S_4 \rangle}{\|S_2\|\|S_4\|} \\ \frac{\langle S_3, S_1 \rangle}{\|S_3\|\|S_1\|} & \frac{\langle S_3, S_2 \rangle}{\|S_3\|\|S_2\|} & 1 & \frac{\langle S_3, S_4 \rangle}{\|S_3\|\|S_4\|} \\ \frac{\langle S_4, S_1 \rangle}{\|S_4\|\|S_1\|} & \frac{\langle S_4, S_2 \rangle}{\|S_4\|\|S_2\|} & \frac{\langle S_4, S_3 \rangle}{\|S_4\|\|S_3\|} & 1 \end{bmatrix}$$

$\frac{|\langle S_i, S_j \rangle|}{\|S_i\|\|S_j\|} \approx 1 \Rightarrow$ linear dependence $\frac{|\langle S_i, S_j \rangle|}{\|S_i\|\|S_j\|} \approx 0 \Rightarrow$ linear independence

Nonlinear Identifiability Analysis

Decomposition of $S^T S = D^T C D$

$\frac{|\langle S_i, S_j \rangle|}{||S_i|| \, ||S_j||} \approx 1 \Rightarrow$ linear dependence $\qquad \frac{|\langle S_i, S_j \rangle|}{||S_i|| \, ||S_j||} \approx 0 \Rightarrow$ linear independence

Example: UDDS Drive Cycle Applied to Battery Model

$$C = \begin{bmatrix} 1 & -0.3000 & 0.2908 & 0.2956 \\ -0.3000 & 1 & -0.9801 & -0.9805 \\ 0.2908 & -0.9801 & 1 & 0.9322 \\ 0.2956 & -0.9805 & 0.9322 & 1 \end{bmatrix}$$

$\theta_2, \theta_3, \theta_4$ are linearly dependent
Identify the subset $\theta_h = [\theta_1, \theta_4]^T$ via nonlinear least squares

- $\theta_1 = n_{Li}$: Capacity Fade
- $\theta_4 = R_f$: Power Fade

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Remarks on extensions to high-dimensional parameter spaces

- Orthogonalization and permutation of $S^T S$ to rank sensitivity
- Min parameter variance via Cramer-Rao inequality to rank certainty