Adaptive Estimation and Control of Models for Battery Electrochemistry

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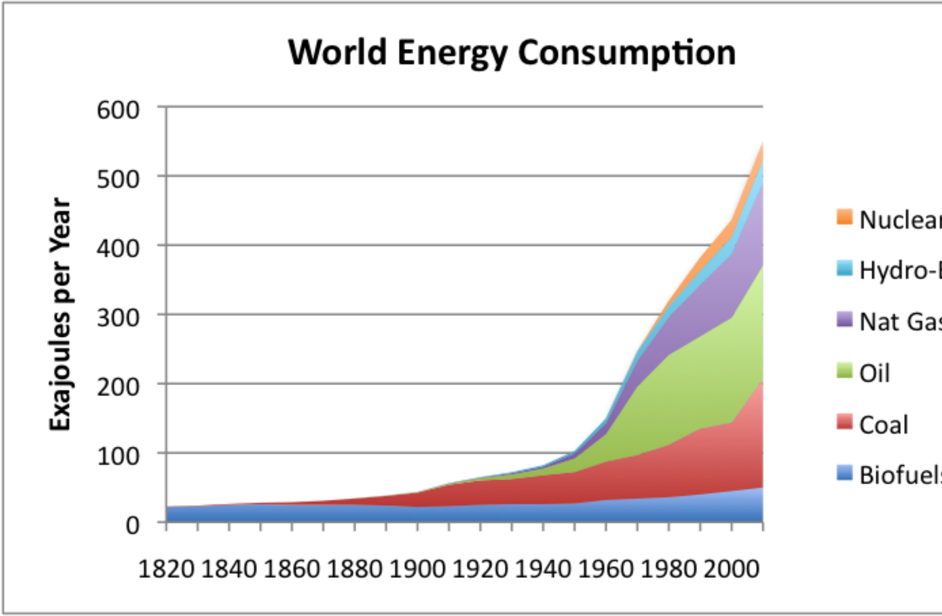
Core Philosophy:

$$(\text{Dynamical models of physical phenomena})$$
$$+ \, (\text{novel control paradigms})$$
$$= (\text{transformative advancements})$$



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

Zero emissions vehicle (ZEV)

33% renewables by 2020

Go Solar California

Energy Crisis Solutions

Energy storage	Demand-side 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
2. Demand Response in Smart Grids
3. Future

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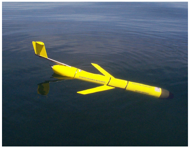
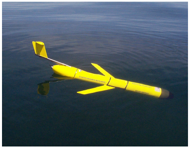
A Golden Era

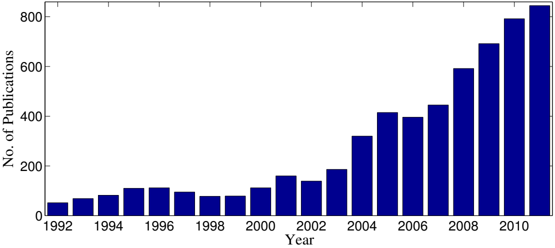

ST. JUDE MEDICAL
Sylmar, CA USA
ACCENT SR RF
PM1210 SSR
ST. JUDE MEDICAL
Sylmar, CA USA
ANTHEM RF
PM3212 DDDRV



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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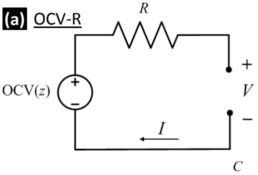
Battery Models

Equivalent Circuit Model

(a) OCV-R



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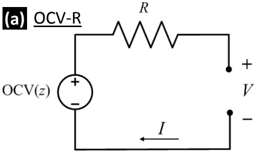
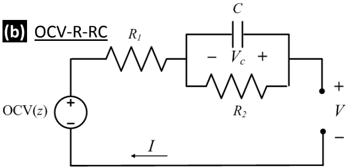
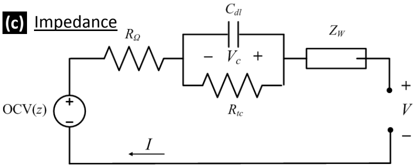


(b) OCV-R-RC



(c) Impedance



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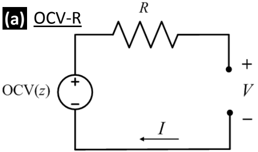

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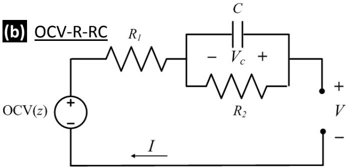

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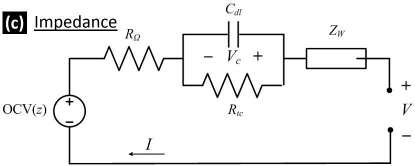
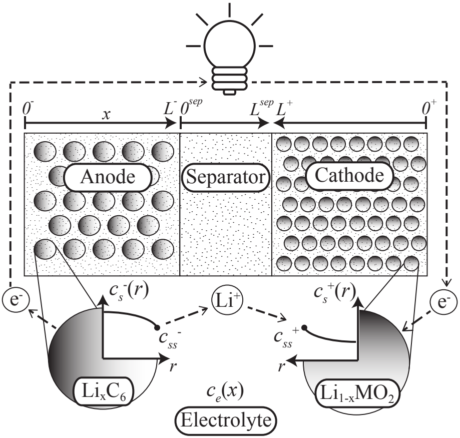
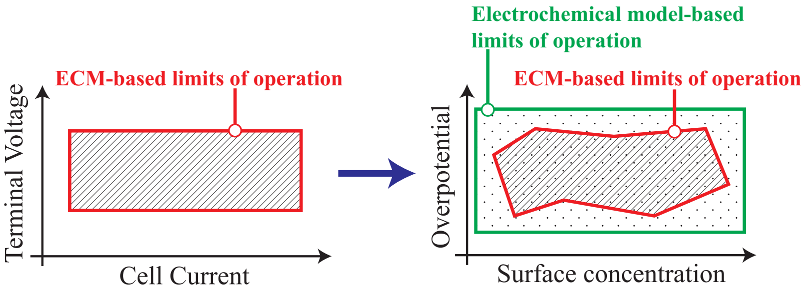


Electrochemical Model



Operate Batteries at their Physical Limits



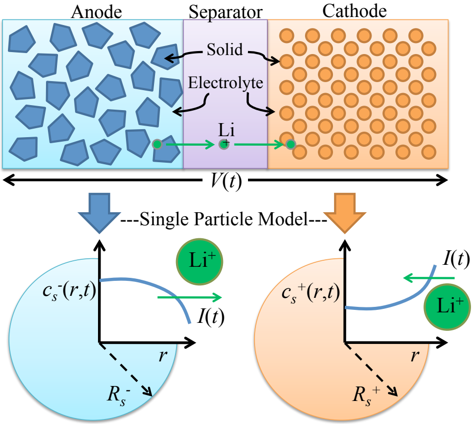
Electrochemical Model Equations

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:

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

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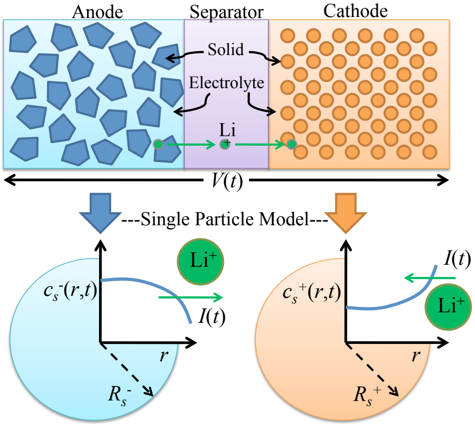

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Boundary conditions:

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

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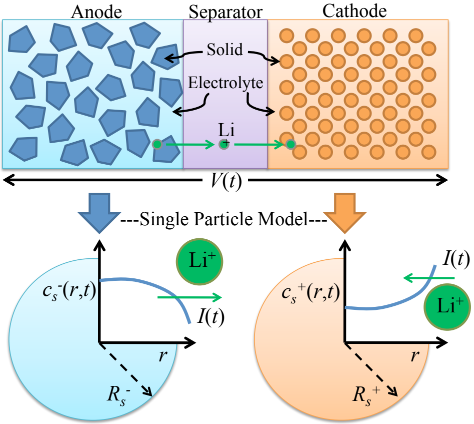

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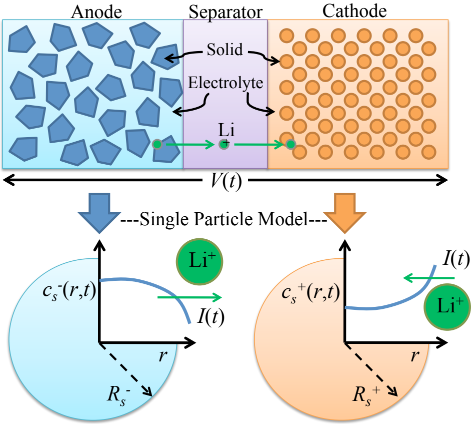
Voltage Output Function:

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



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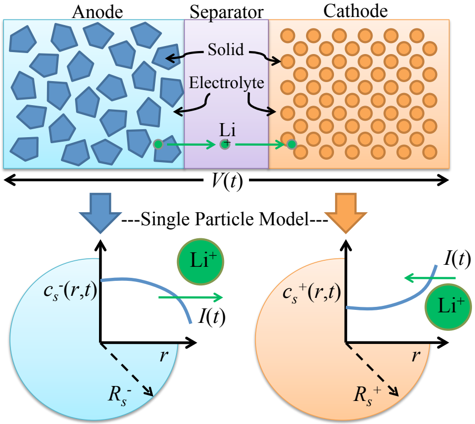

Definitions

- 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

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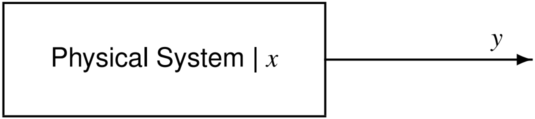
Intro to Estimation



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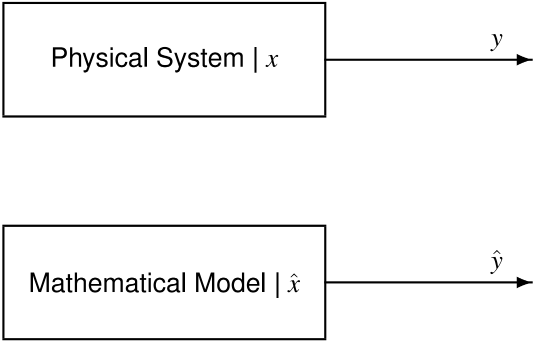

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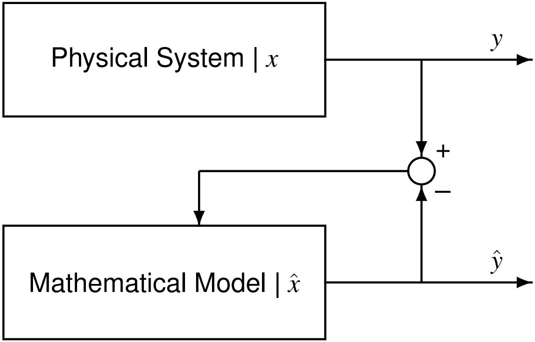

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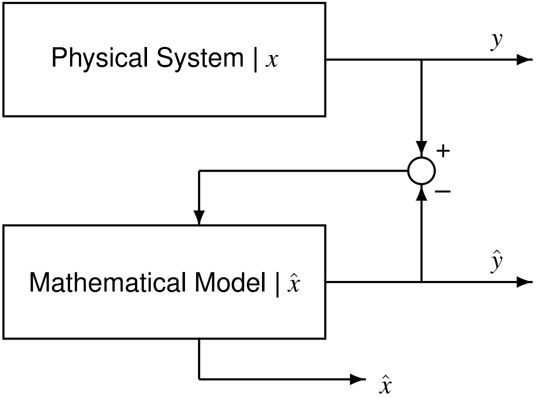

Backstepping PDE Estimator

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

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

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

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

The Concept

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

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

$$\tilde{w}(0,t) = 0 \qquad W(t) = \frac{1}{2}\int_0^1 \tilde{w}^2(x,t)dx$$

$$\frac{\partial \tilde{w}}{\partial r}(1,t) = \frac{1}{2}\tilde{w}(1,t) \qquad \dot{W}(t) \leq -\gamma W(t)$$

Backstepping PDE Estimator

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

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\end{aligned}$$

Kernel PDE

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

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

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

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

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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

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

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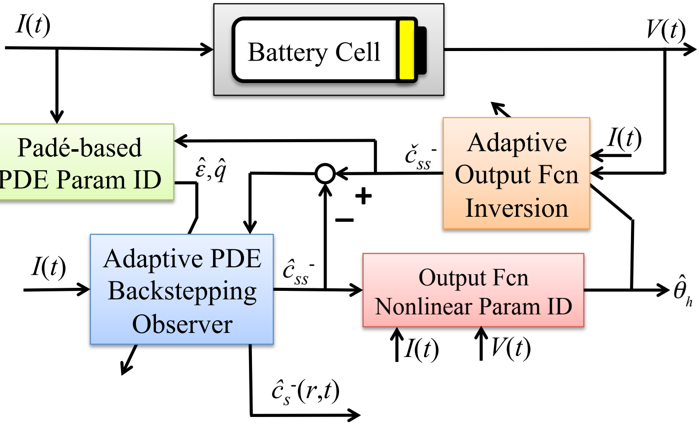
Relate uncertain parameters to SOH-related concepts

- Capacity fade
- Power fade

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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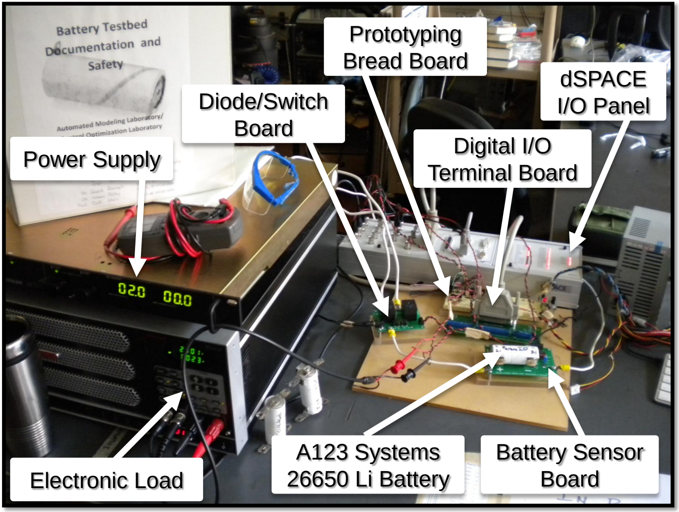
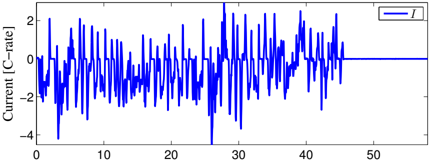
Apply nonlinear recursive least squares to θ_h

Custom-Built Battery-in-the-Loop Testbed



Results

UDDS Drive Cycle Input



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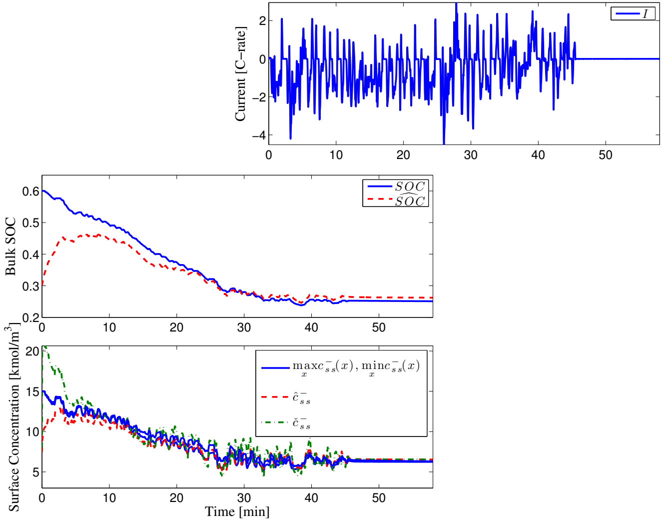

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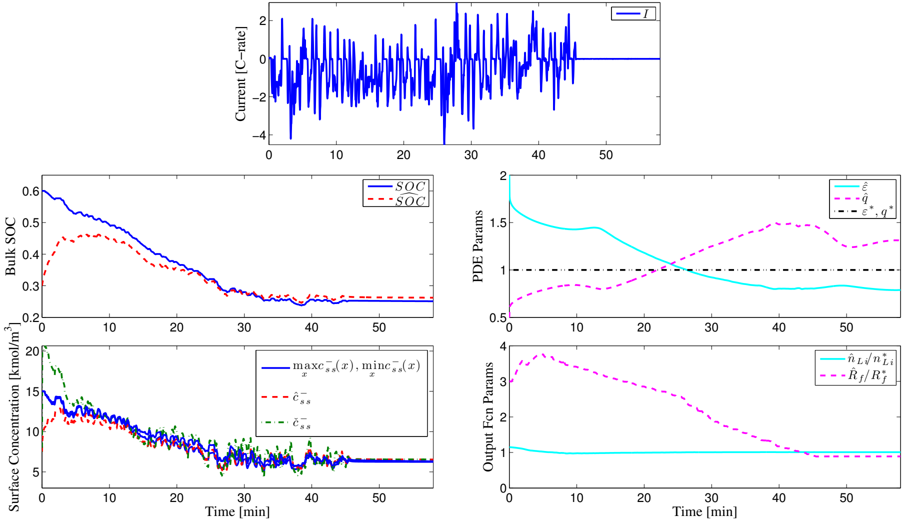
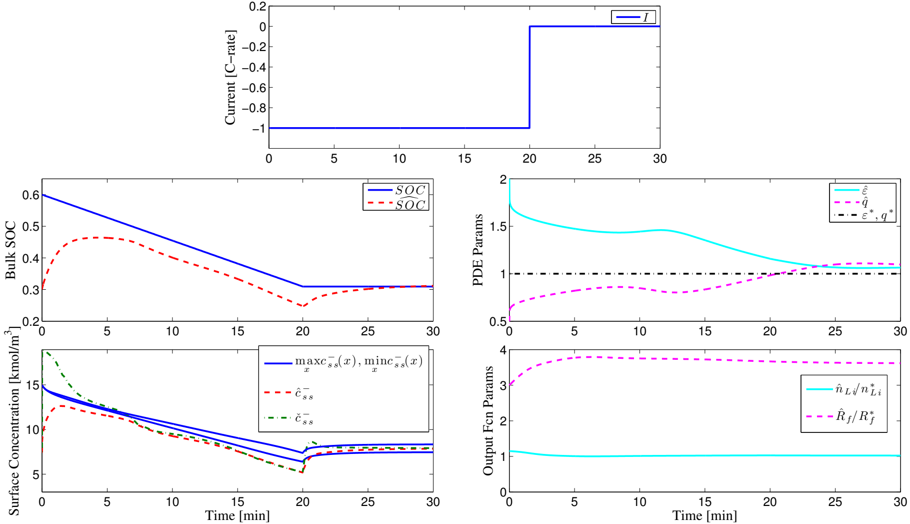


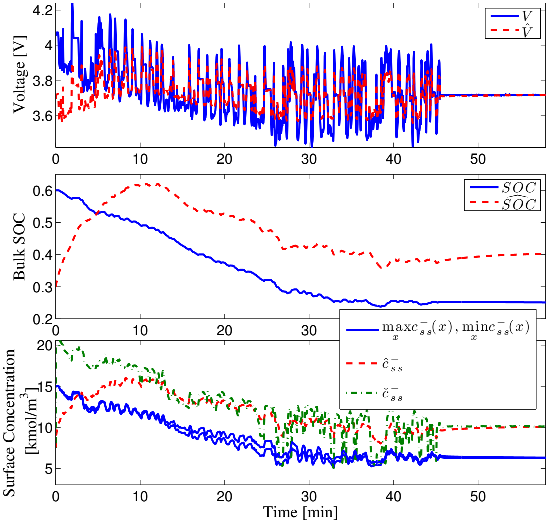
Results

Constant 1C Discharge

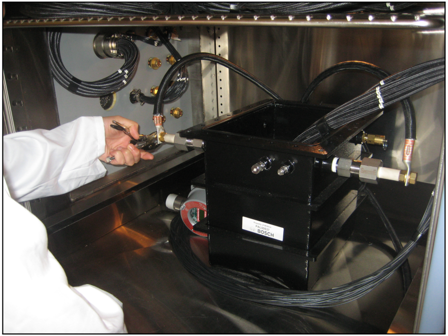


Results

No Parameter Adaption - Bias in State Estimates



Experimental Testing | ARPA-E AMPED Program



Outline

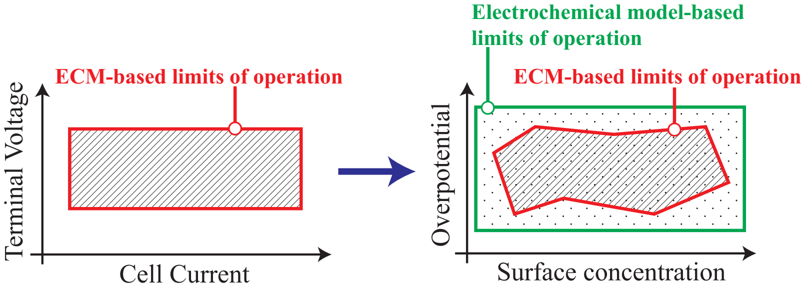
1. Batteries
   - [Electrochemical Modeling] Incorporating Physics
   - [SOC/SOH Estimation] Looking Inside w/ Models, Meas., and Math
   - [Constrained Control] Operate at the Limits, Safely
2. Demand Response in Smart Grids
3. Future

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.

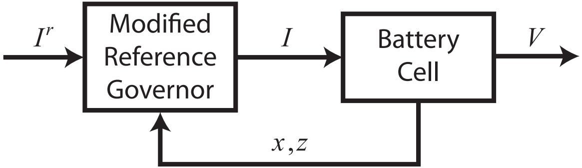


Constraints

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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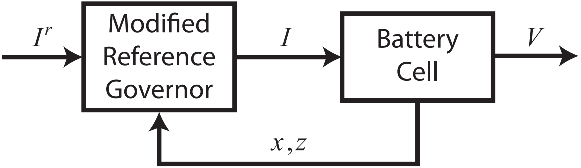

MRG Equations

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

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

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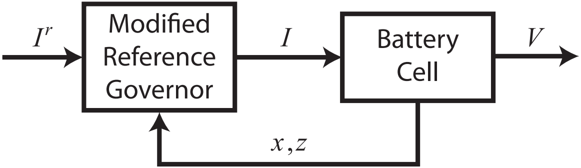

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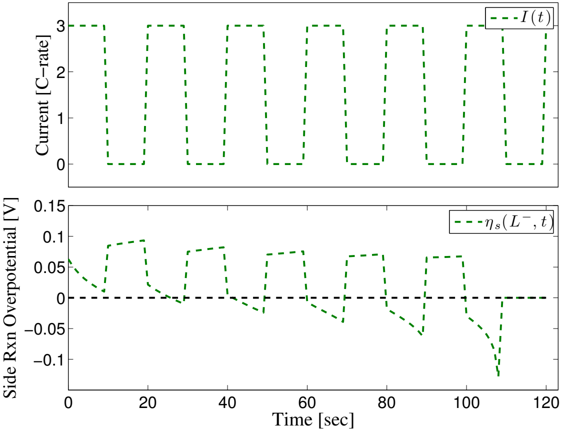
Def'n: Admissible Set $\mathcal{O}$

$$\mathcal{O} = \left\{ (x(t), z(t)) : y(\tau) \in \mathcal{Y}, \forall \tau \in [t, t+T_s] \right\}$$

$$\begin{aligned} \dot{x}(t) &= f(x(t), z(t), \beta I^r) \\ 0 &= g(x(t), z(t), \beta I^r) \\ y(t) &= C_1 x(t) + C_2 z(t) + D \cdot \beta I^r + E \end{aligned}$$

Constrained Control of EChem States



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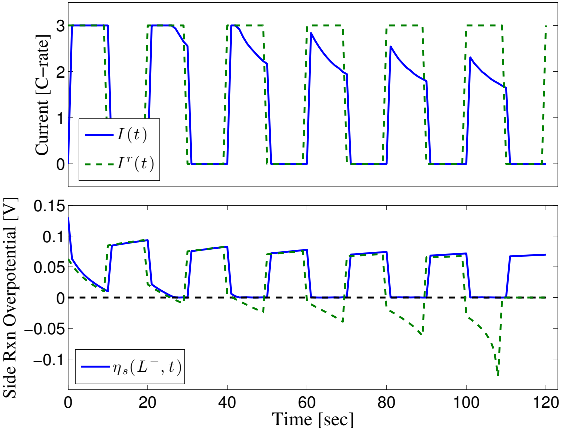
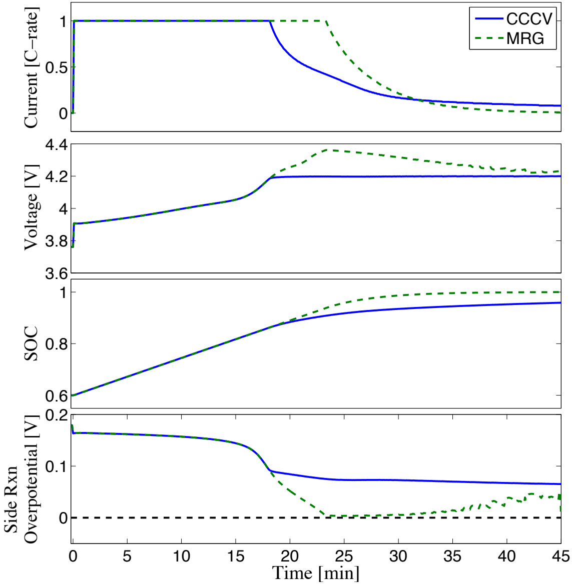


Application to Charging



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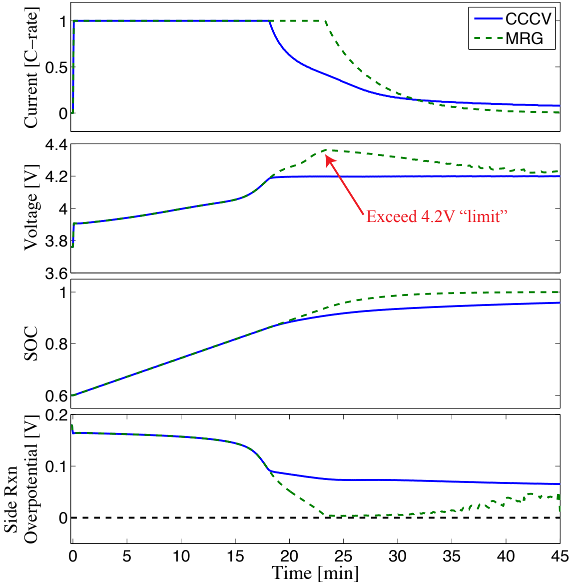

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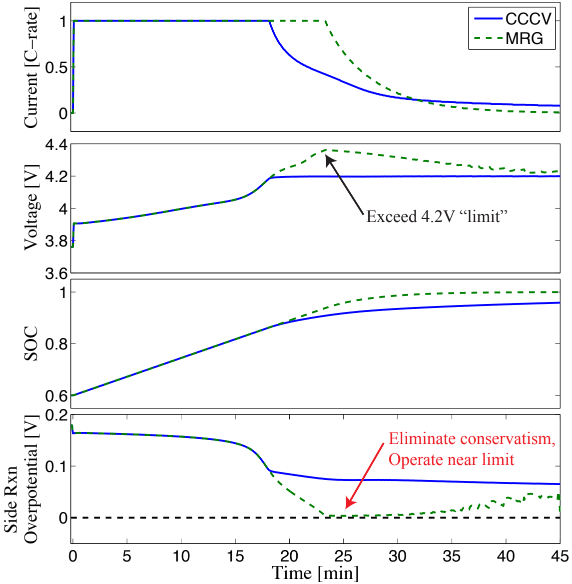

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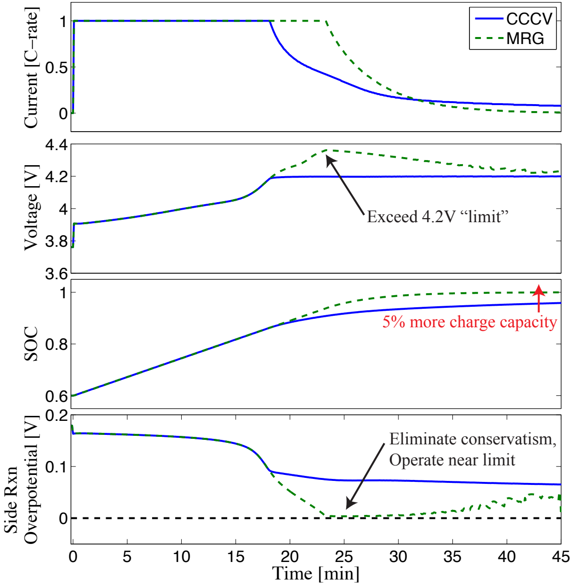

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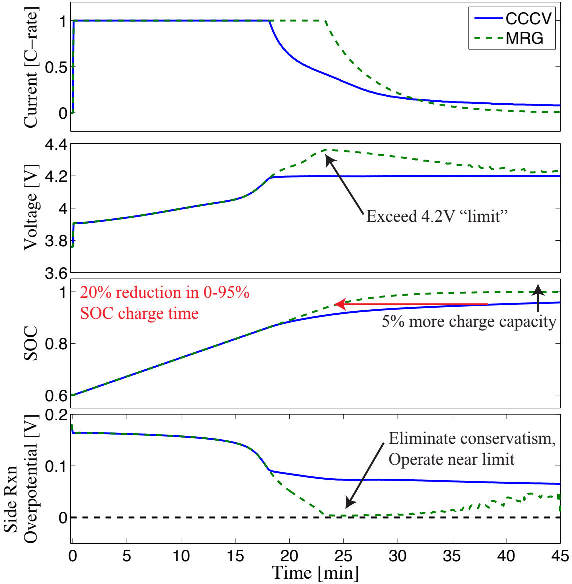
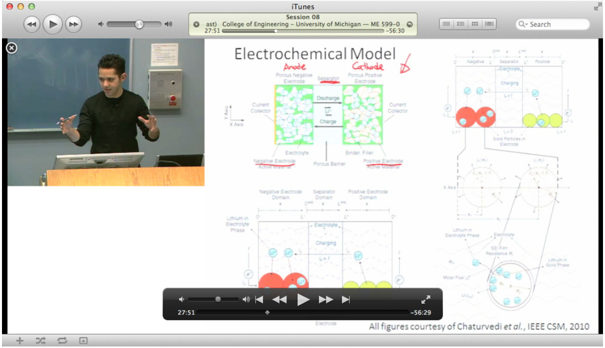


Enrollment

- 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.

Impact through education.

Energy Crisis Solutions

Energy storage	Demand-side management
(e.g., batteries)	(e.g., smart grids)

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Outline

The Renewable Integration Problem

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

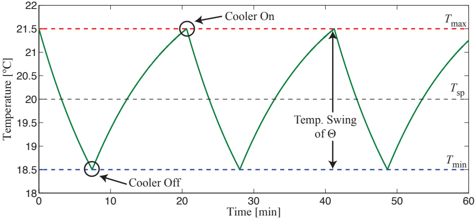
Flexible loads (e.g. TCLs) can absorb variability in renewable generation

Modeling Aggregations of TCLs

Individual TCL models

$\Downarrow$

(Tens of) Thousands of hybrid ODEs



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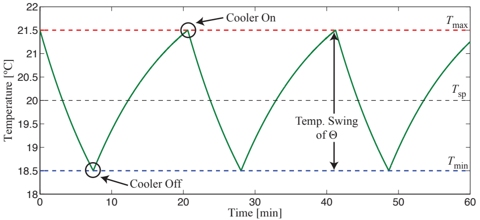
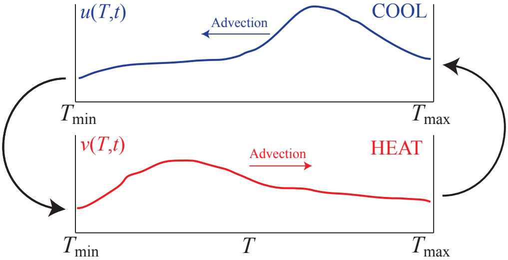


Model **aggregations** of TCLs
⇓
Two coupled linear PDEs

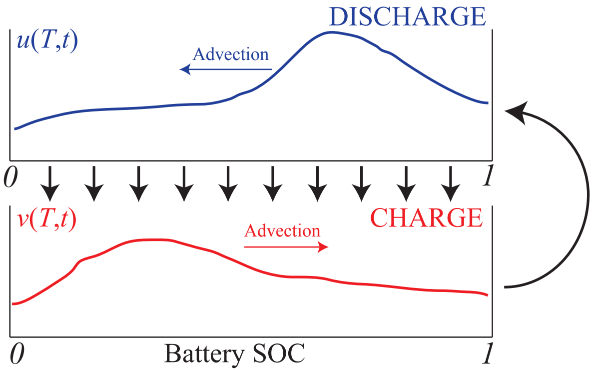


$u(T,t)$	# TCLs/°C, in COOL state, @ temp T, time t
$v(T,t)$	# TCLs/°C, in HEAT state, @ temp T, time t

Modeling Aggregated PEVs

Main Idea: Mathematically model as coupled linear PDEs

$u(T,t)$	# PEVs / SOC, in DISCHARGE state, @ SOC x, time t
$v(T,t)$	# PEVs / SOC, in CHARGE state, @ SOC x, time t

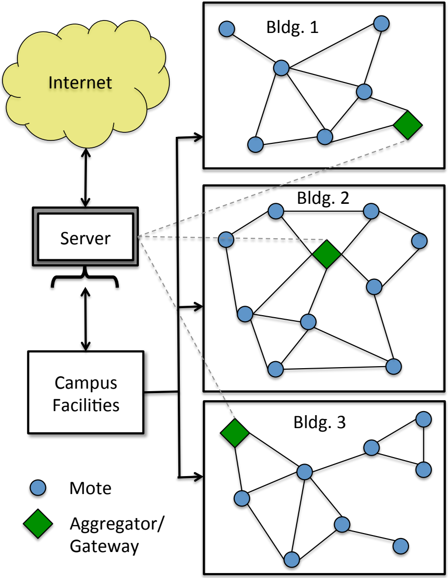


University Campus: A Living Laboratory

Goal: Smart Campus

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

Libelium Waspmotes and Meshlium Gateway



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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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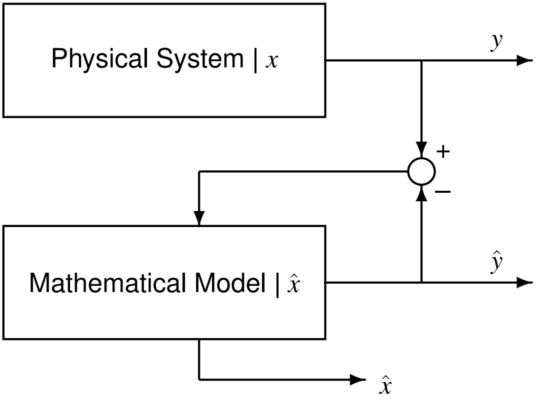

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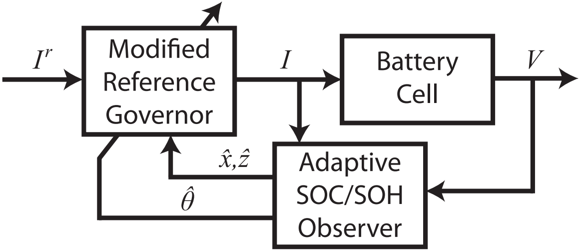

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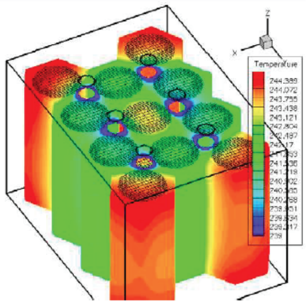
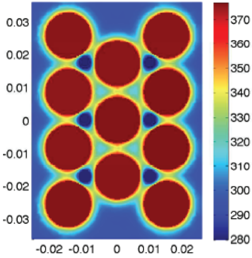


CFD simulation



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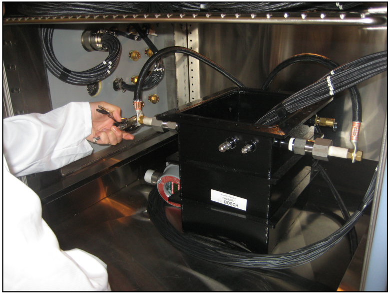

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Funding:

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- DoD HESM

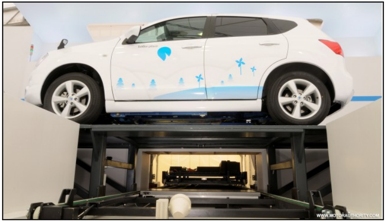
Future: Solve EV Mobility - Modular Battery Packs

Goal: Solve range anxiety

Future: Solve EV Mobility - Modular Battery Packs

Fast Charging

Battery Swapping



Future: Solve EV Mobility - Modular Battery Packs

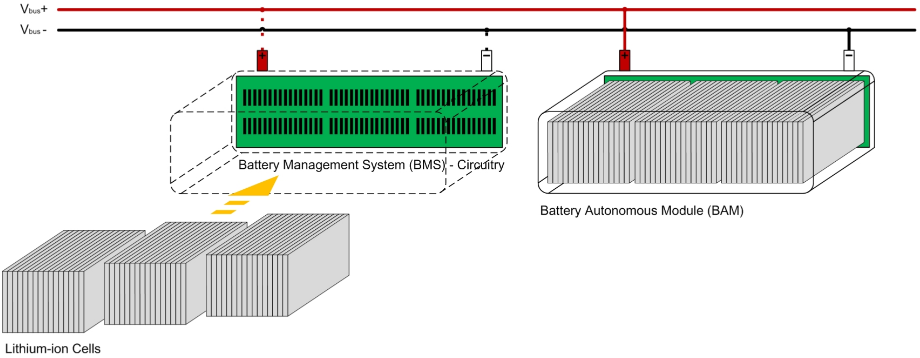
Modular User-Replaceable Batts

Scalable to EVs?

Future: Solve EV Mobility - Modular Battery Packs

Key components:

(1) Battery Autonomous Architecture (BAM)



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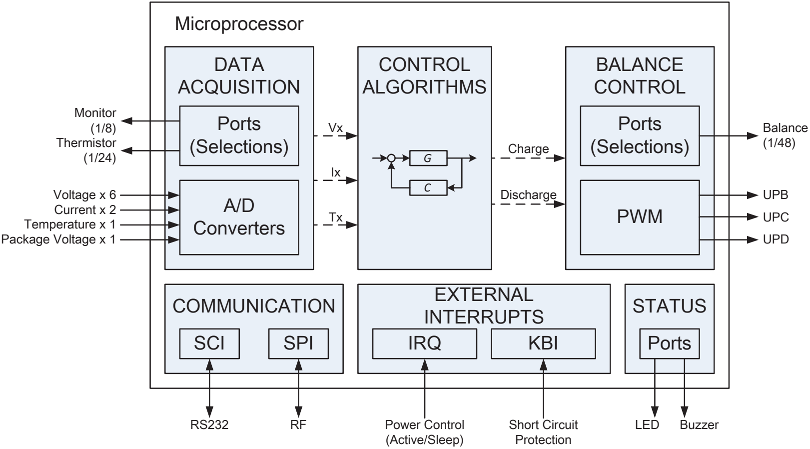

Future: Solve EV Mobility - Modular Battery Packs

Key components:
(1) Battery Autonomous Architecture (BAM)
(2) Battery Management System (BMS)
(3) Economics $\leftrightarrow$ Design

- Financial model?
- Lease from third-party owner?
- Lower acquisition & operational costs?

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- ARPA-E RANGE
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Apps: Buildings & PEVs

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(1) System ID & State Estimation

$$u_t(x,t) = \alpha\lambda(x)u_x + \alpha u + \beta u_{xx}$$
$$v_t(x,t) = -\alpha\mu(x)v_x + \alpha v + \beta v_{xx}$$
$$u(1,t) = q_1 v(1,t), \qquad u_x(0,t) = -v_x(0,t)$$
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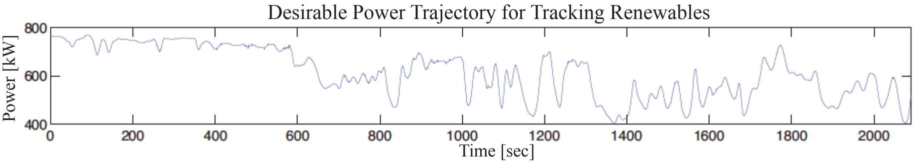

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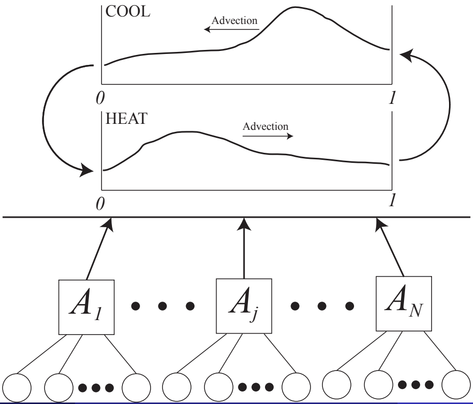
(3) Hierarchical Control Architecture



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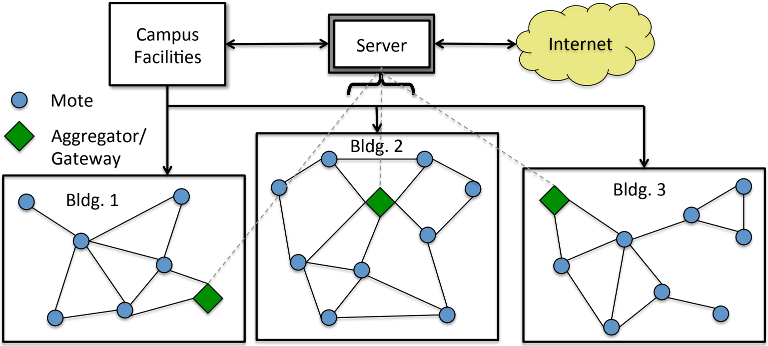

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Funding:

- DOE EERE
- NSF EPAS, CPS

Courses I could teach

24-311 Numerical Methods

24-351 Dynamics

24-352 Dynamic Systems & Control

24-422 Special Topics in Energy Systems Modeling

24-451 Feedback Control Systems

24-643 Special Topics in Electrochemical Energy Storage Systems

24-671 Special Topics in Practical Control and Automation

24-701 Mathematical Techniques in Engineering

24-703 Numerical Methods in Engineering

24-771 Linear Systems

24-776 Nonlinear Controls

NEW - Battery Systems and Control

NEW - Control of Distributed Parameter Systems

my lab...

Themes: systems & control | energy storage & smart grids

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Key Tools:

- PDE modeling
- Lyapunov stability
- Adaptive control
- Optimization

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Potential Affiliations

- Scott Institute for Energy Innovation
- Carnegie Mellon Electricity Industry Center
- Vehicle Electrification Group

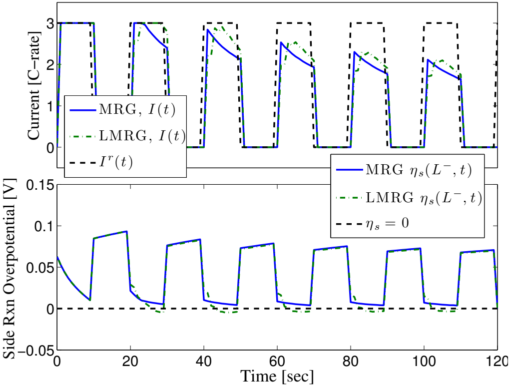
Publications available at

http://flyingv.ucsd.edu/smoura/

smoura@ucsd.edu

Linear Modified Reference Governor

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



PHEV Power Management

Problem Statement

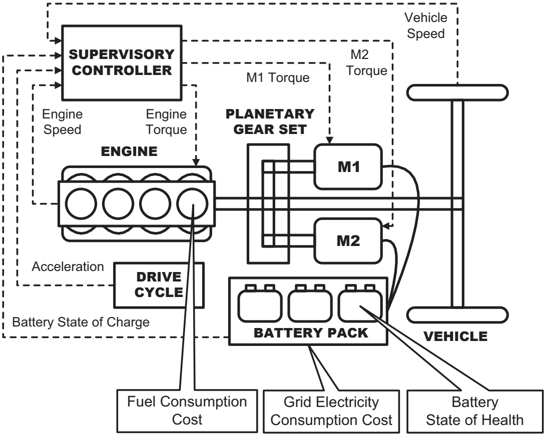
Design a supervisory control algorithm for plug-in hybrid electric vehicles (PHEVs) that splits engine and battery power in some optimal sense.

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

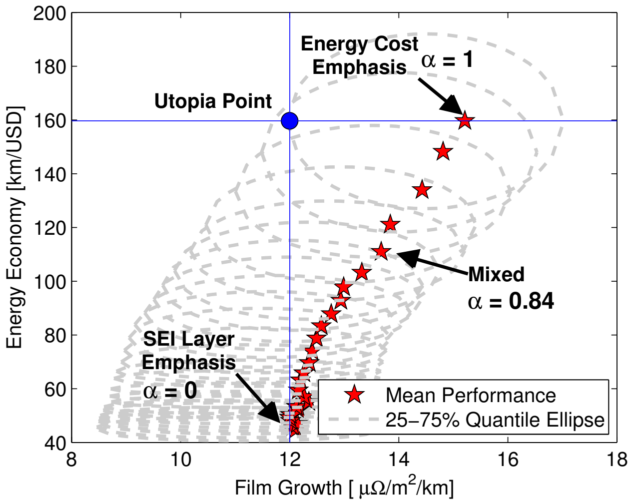
- Control Inputs
  - Engine Torque
  - M1 Torque
- State Variables
  - Engine speed
  - Vehicle speed
  - Battery SOC
  - Vehicle acceleration (Markov Chain)



Control Optimization: Minimize energy consumption cost AND battery aging

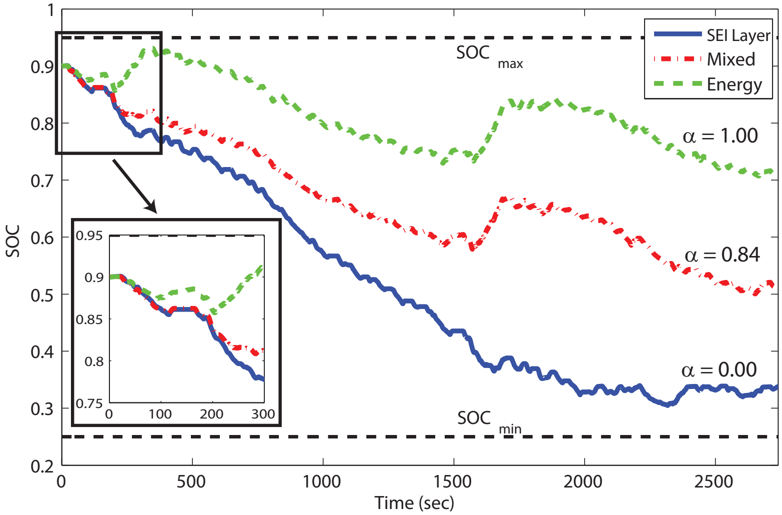
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth

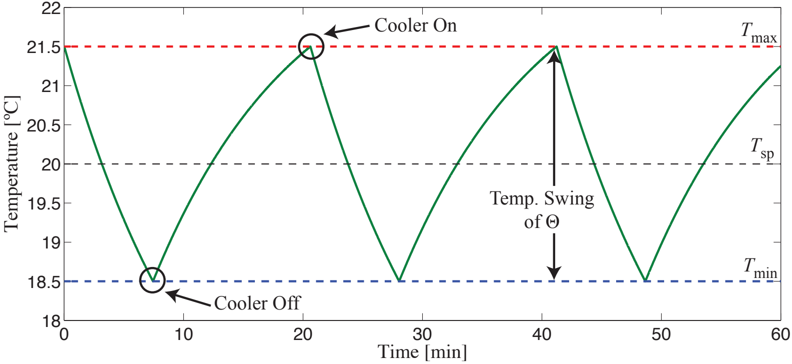


SOC Trajectories

Anode-side SEI Layer Growth | UDDSx2



Modeling TCLs



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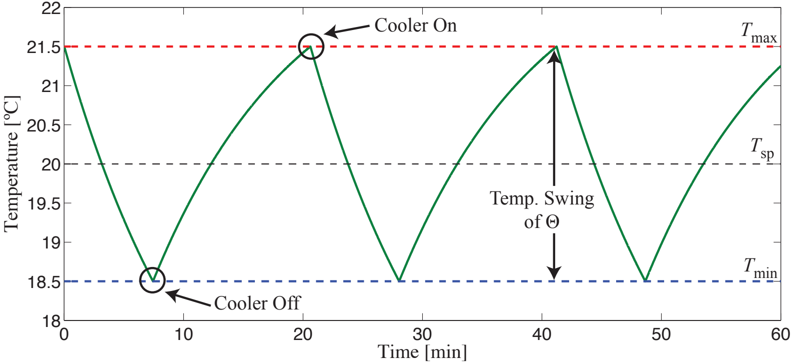

$$\dot{T}_i(t) = \frac{1}{R_i C_i}\left[T_\infty - T_i(t) - s_i(t) R_i P_i\right], \quad i = 1, 2, \ldots, N$$

$$s_i \in \{0, 1\}$$

Modeling Aggregated TCLs

Main Idea: Convert 1000+ ODEs into two coupled linear PDEs

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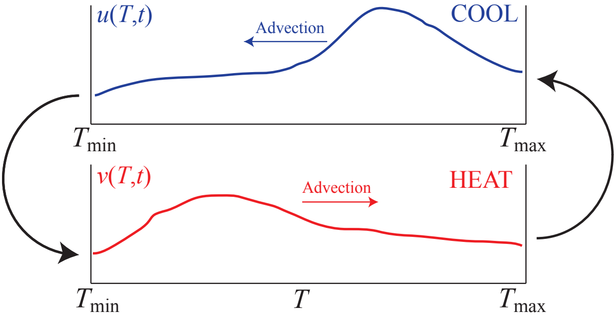

Modeling Aggregated TCLs

Main Idea: Convert 1000+ ODEs into two coupled linear PDEs

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Flux of TCLs in HEAT state:
#TCLs / sec

$$\psi(T,t) = v(T,t)\frac{dT}{dt}(t) = \frac{1}{RC}\left[T_\infty - T(t)\right] v(T,t)$$

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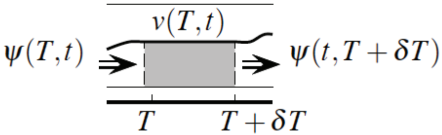

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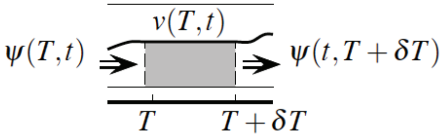
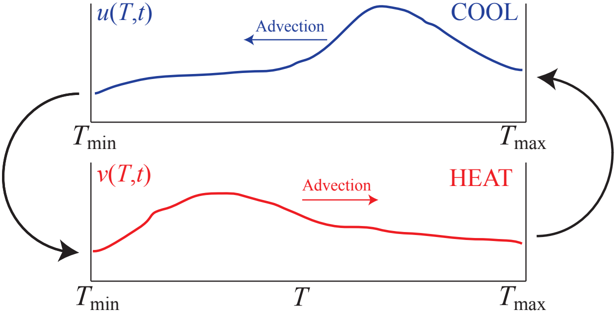


$$\begin{aligned}
\frac{\partial v}{\partial t}(T,t) &= \lim_{\delta T \to 0}\left[\frac{\psi(T+\delta T,t) - \psi(T,t)}{\delta T}\right] \\
&= \frac{\partial \psi}{\partial T}(T,t) \\
&= -\frac{1}{RC}\left[T_\infty - T(t)\right]\frac{\partial v}{\partial T}(T,t) + \frac{1}{RC}v(T,t)
\end{aligned}$$

PDE Model of Aggregated TCLs



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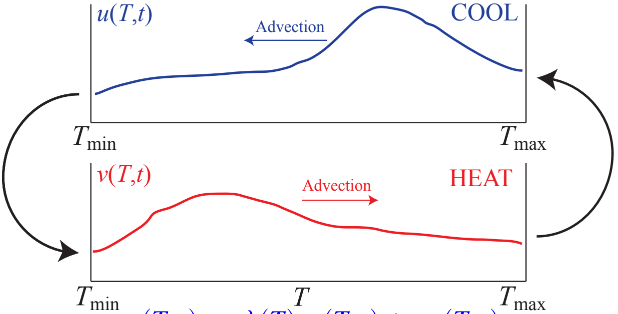


$$u_t(T,t) = \alpha\lambda(T)u_T(T,t) + \alpha u(T,t)$$

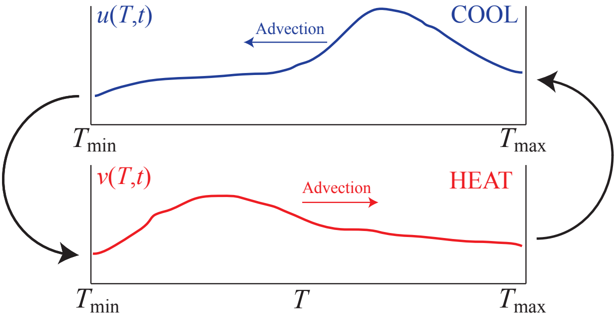
$$v_t(T,t) = -\alpha\mu(T)v_T(T,t) + \alpha v(T,t)$$

$$u(T_{\max},t) = q_1 v(T_{\max},t)$$

$$v(T_{\min},t) = q_2 u(T_{\min},t)$$

Video of 1,000 TCLs

PDE Model of Aggregated TCLs



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Original Idea: Malhame and Chong, Trans. on Automatic Control (1985)
Remark: Assumes homogeneous populations

Modeling Heterogeneous Aggregated TCLs

Reality: TCL populations are heterogeneous
e.g. variable heat capacity, power, deadband sizes

Video of 1,000 heterogeneous TCLs

Modeling Heterogeneous Aggregated TCLs

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e.g. variable heat capacity, power, deadband sizes

$$
\begin{aligned}
u_t(T,t) &= \alpha\lambda(T)u_T(T,t) + \alpha u(T,t) + \beta u_{TT}(T,t) \\
v_t(T,t) &= -\alpha\mu(T)v_T(T,t) + \alpha v(T,t) + \beta v_{TT}(T,t) \\
u(T_{\max},t) &= q_1 v(T_{\max},t), \qquad u_T(T_{\min},t) = -v_T(T_{\min},t) \\
v(T_{\min},t) &= q_2 u(T_{\min},t), \qquad v_T(T_{\max},t) = -u_T(T_{\max},t)
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$$

Modeling Heterogeneous Aggregated TCLs

Reality: TCL populations are heterogeneous
e.g. variable heat capacity, power, deadband sizes

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v(T_{\min},t) &= q_2 u(T_{\min},t), \qquad v_T(T_{\max},t) = -u_T(T_{\max},t)
\end{aligned}
$$

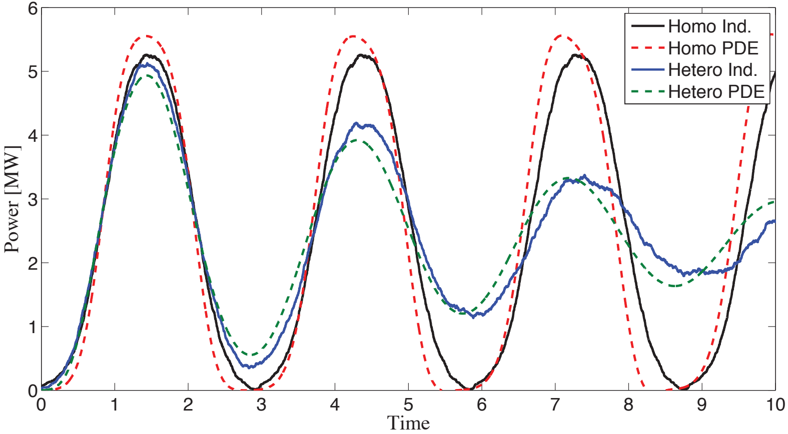
Proposition: The total number of TCLs is conserved over time.

$$
Q(t) = \int_{T_{\min}}^{T_{\max}} u(T,t)dT + \int_{T_{\min}}^{T_{\max}} v(T,t)dT
$$

$$
\frac{dQ}{dt}(t) = 0, \qquad \forall t
$$

Video Evolution of Heterogeneous PDE

Model Comparison



Outline

- Estimation - looking inside w/ Models, Meas., and Math

The State Estimation Problem

Question: Possible to monitor TCLs with minimal sensing infrastructure?

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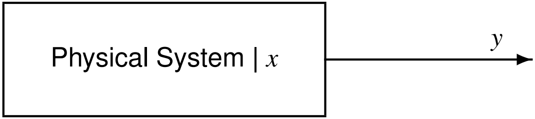

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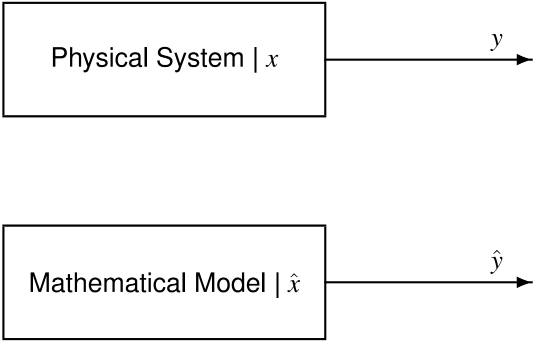

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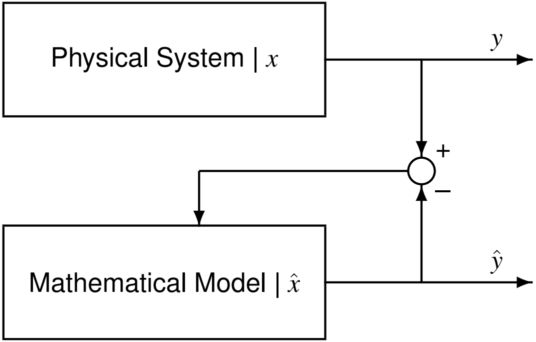

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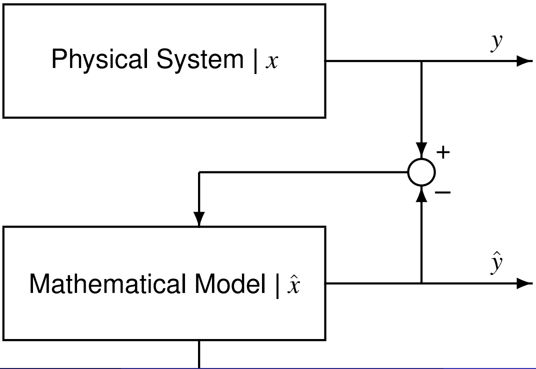

PDE State Estimator

Heterogeneous PDE Model: (u, v)

$$
\begin{aligned}
u_t(x,t) &= \alpha\lambda(x)u_x + \alpha u + \beta u_{xx} \\
v_t(x,t) &= -\alpha\mu(x)v_x + \alpha v + \beta v_{xx} \\
u(1,t) &= q_1 v(1,t), \qquad u_x(0,t) = -v_x(0,t) \\
v(0,t) &= q_2 u(0,t), \qquad v_x(1,t) = -u_x(1,t)
\end{aligned}
$$

PDE State Estimator

Estimator: $(\hat{u}, \hat{v})$

$$
\begin{aligned}
\hat{u}_t(x,t) &= \alpha\lambda(x)\hat{u}_x + \alpha\hat{u} + \beta\hat{u}_{xx} \\
\hat{v}_t(x,t) &= -\alpha\mu(x)\hat{v}_x + \alpha\hat{v} + \beta\hat{v}_{xx} \\
\hat{u}(1,t) &= q_1 v(1,t), \qquad \hat{u}_x(0,t) = -\hat{v}_x(0,t) + p_{10}\left[u(0,t) - \hat{u}(0,t)\right] \\
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\end{aligned}
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PDE State Estimator

Estimator: $(\hat{u}, \hat{v})$

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\end{aligned}
$$

Estimation Error Dynamics: $(\tilde{u}, \tilde{v}) = (u - \hat{u}, v - \hat{v})$

$$
\begin{aligned}
\tilde{u}_t(x,t) &= \alpha\lambda(x)\tilde{u}_x + \alpha\tilde{u} + \beta\tilde{u}_{xx} \\
\tilde{v}_t(x,t) &= -\alpha\mu(x)\tilde{v}_x + \alpha\tilde{v} + \beta\tilde{v}_{xx} \\
\tilde{u}(1,t) &= 0, \qquad \tilde{u}_x(0,t) = -\tilde{v}_x(0,t) - p_{10}\tilde{u}(0,t) \\
\tilde{v}(0,t) &= 0, \qquad \tilde{v}_x(1,t) = -\tilde{u}_x(1,t) - p_{20}\tilde{v}(1,t)
\end{aligned}
$$

Goal: Pick $p_{10}, p_{20} \in \mathbb{R}$ such that $(\tilde{u}, \tilde{v}) = (0,0)$ is exponentially stable in $\mathcal{L}_2$-norm

Lyapunov Stability Analysis

Consider the $\mathcal{L}_2$-norm as a candidate Lyapunov functional

$$V(t) = \frac{1}{2}\int_0^1 \tilde{u}(x,t)^2 dx + \frac{1}{2}\int_0^1 \tilde{v}(x,t)^2 dx$$

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The time derivative along the solution trajectories

$$\begin{aligned}\frac{dV}{dt}(t) \leq & \left[-\frac{\alpha}{2}\lambda' - \frac{\beta}{4} + \alpha\right]\int_0^1 \tilde{u}^2 dx + \left[\frac{\alpha}{2}\mu' - \frac{\beta}{4} + \alpha\right]\int_0^1 \tilde{v}^2 dx \\ & + \left[\beta p_{10} - \frac{\alpha}{2}\lambda(0)\right]\tilde{u}^2(0) + \left[-\beta p_{20} + \frac{\alpha}{2}\mu(1)\right]\tilde{v}^2(1)\end{aligned}$$

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Then the evolution of the $\mathcal{L}_2$-norm is bounded as

$$\begin{aligned}\|\tilde{u}(x,t)\|_{\mathcal{L}_2} &\leq \|\tilde{u}(x,0)\|_{\mathcal{L}_2} e^{\left[-\frac{\alpha}{2}\lambda' - \frac{\beta}{4} + \alpha\right]t}, \\ \|\tilde{v}(x,t)\|_{\mathcal{L}_2} &\leq \|\tilde{v}(x,0)\|_{\mathcal{L}_2} e^{\left[\frac{\alpha}{2}\mu' - \frac{\beta}{4} + \alpha\right]t},\end{aligned}$$

Video Evolution of PDE estimator

Key point: Converges to true distribution, using only HVAC on/off signals.