Adaptive Estimation and Control of Models for Battery Electrochemistry

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Cymer Center for Control Systems and Dynamics
UC San Diego

ME Seminar
February 25, 2013



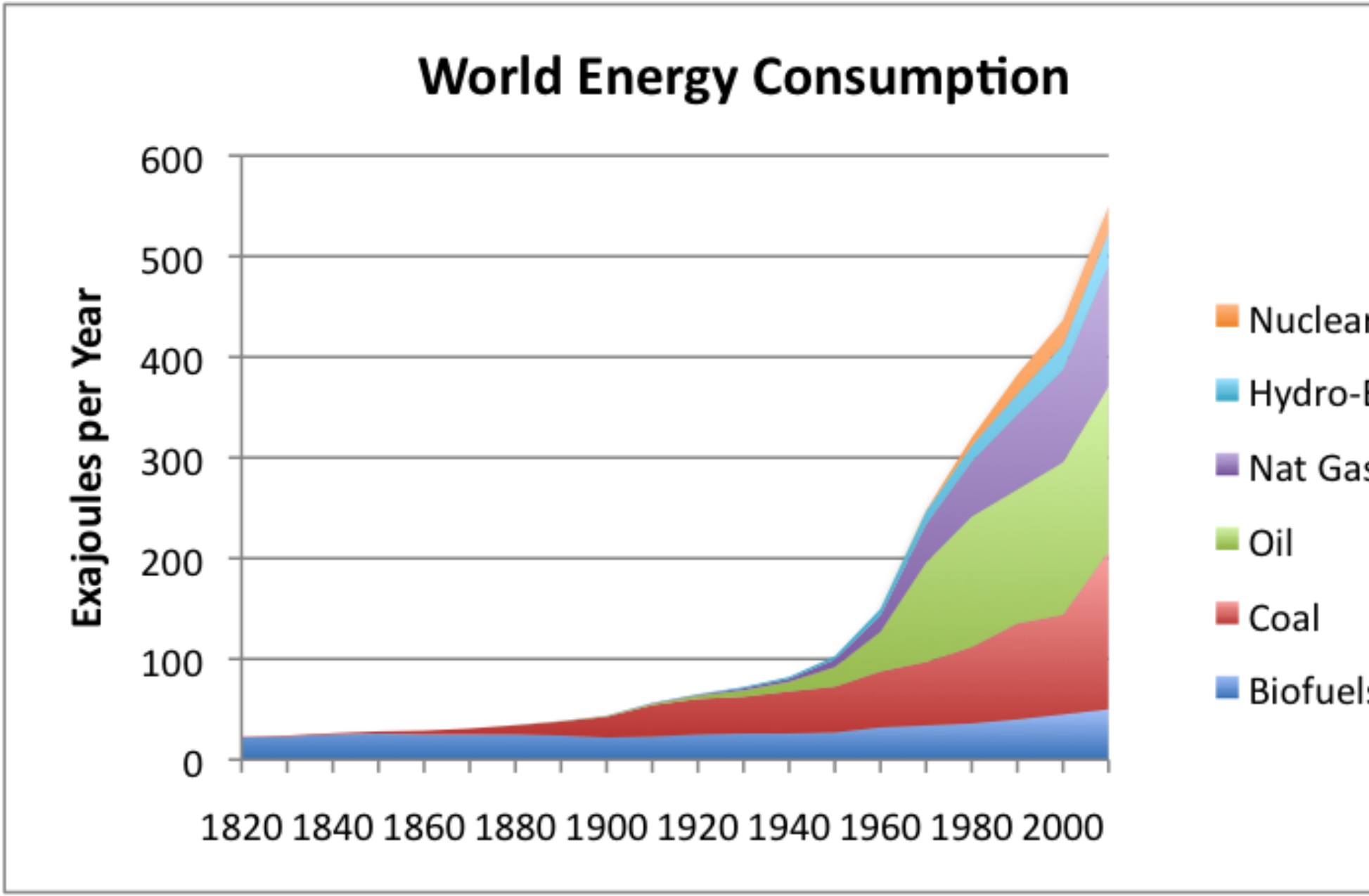
MichiganEngineering

Core Philosophy:

(Dynamical models of physical phenomena)

$+$ (novel control paradigms)

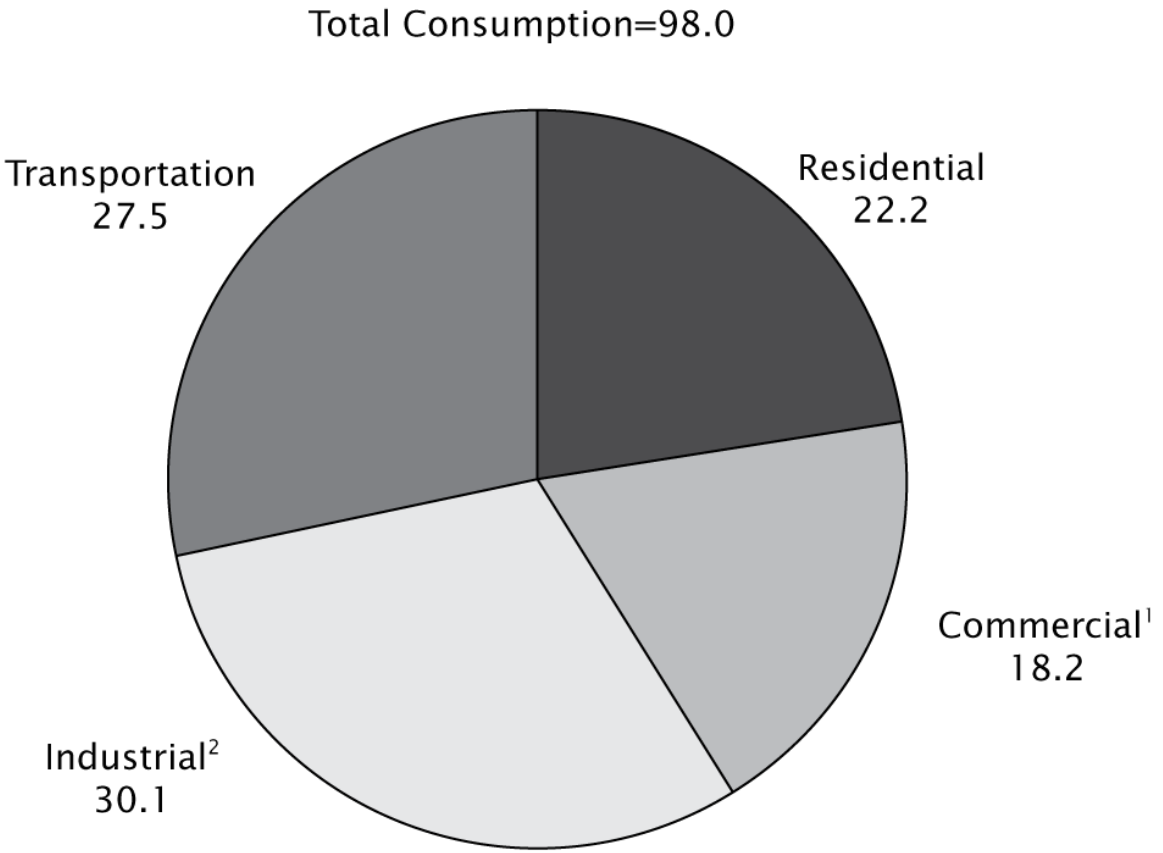
$=$ (transformative advancements)



Vaclav Smil Estimates from Energy Transitions

Energy Consumption by End-Use Sector: 2010

(Quadrillion Btu)



Source: Chart prepared by U.S. Census Bureau.

Energy Initiatives



Denmark 50% wind penetration by 2025

China leads manufacturing of renewable tech

Brazil uses 86% renewables



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
   - [PHEV Power Management] Max eMPG and Max Batt Life
2. Demand Response in Smart Grids
3. Future

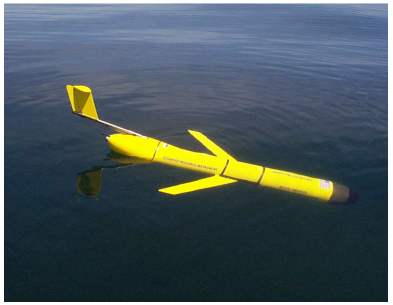
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A Golden Era


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





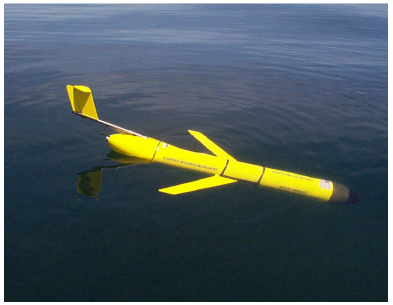




A Golden Era

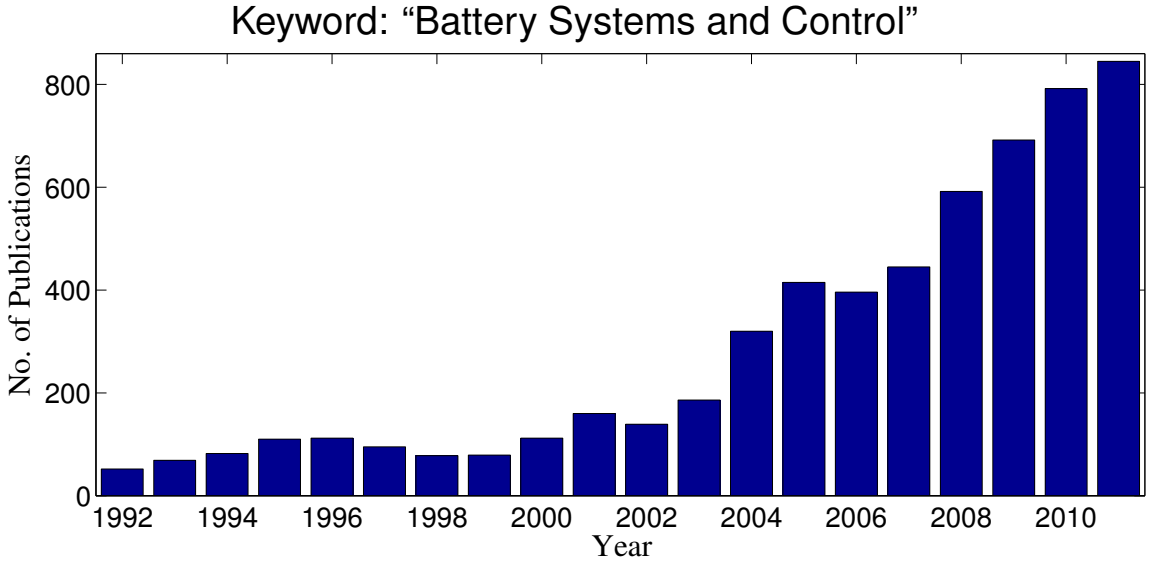

IS-1
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Sylmar, CA USA
ACCENT SR RF
PM1210 SSR
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ANTHEM RF
PM3212 DDDRV










Keyword: “Battery Systems and Control”
No. of Publications
0
200
400
600
800
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
Year

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

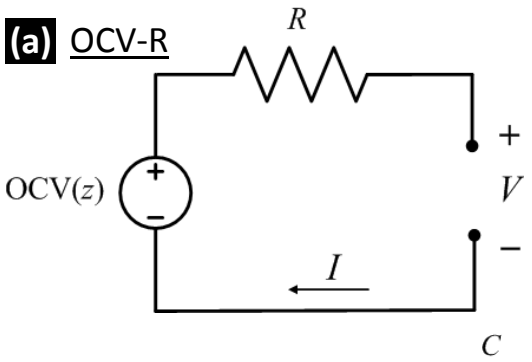
Design better batteries (materials science & chemistry)	Make current batteries better (estimation and control)

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Battery Models

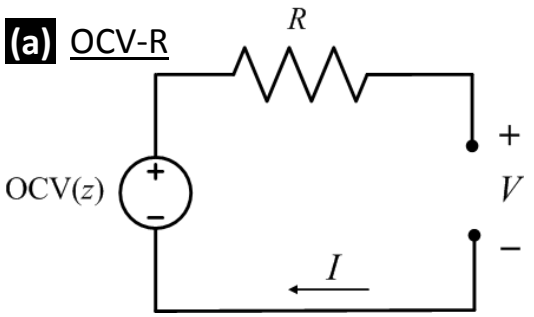
Equivalent Circuit Model



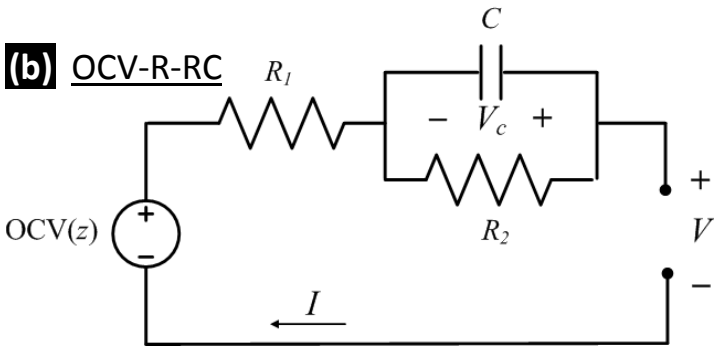
Battery Models

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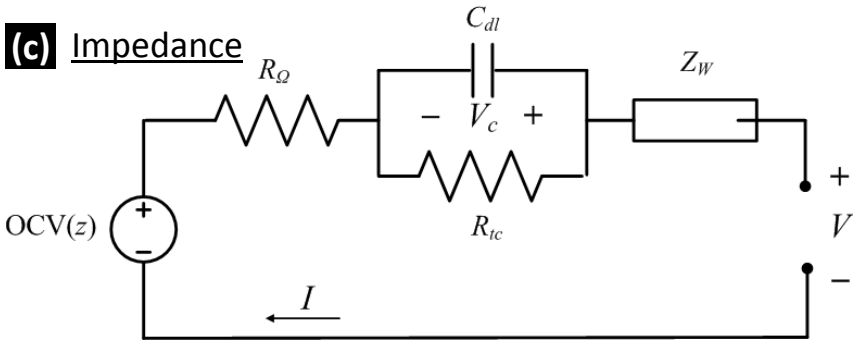
(a) OCV-R



(b) OCV-R-RC

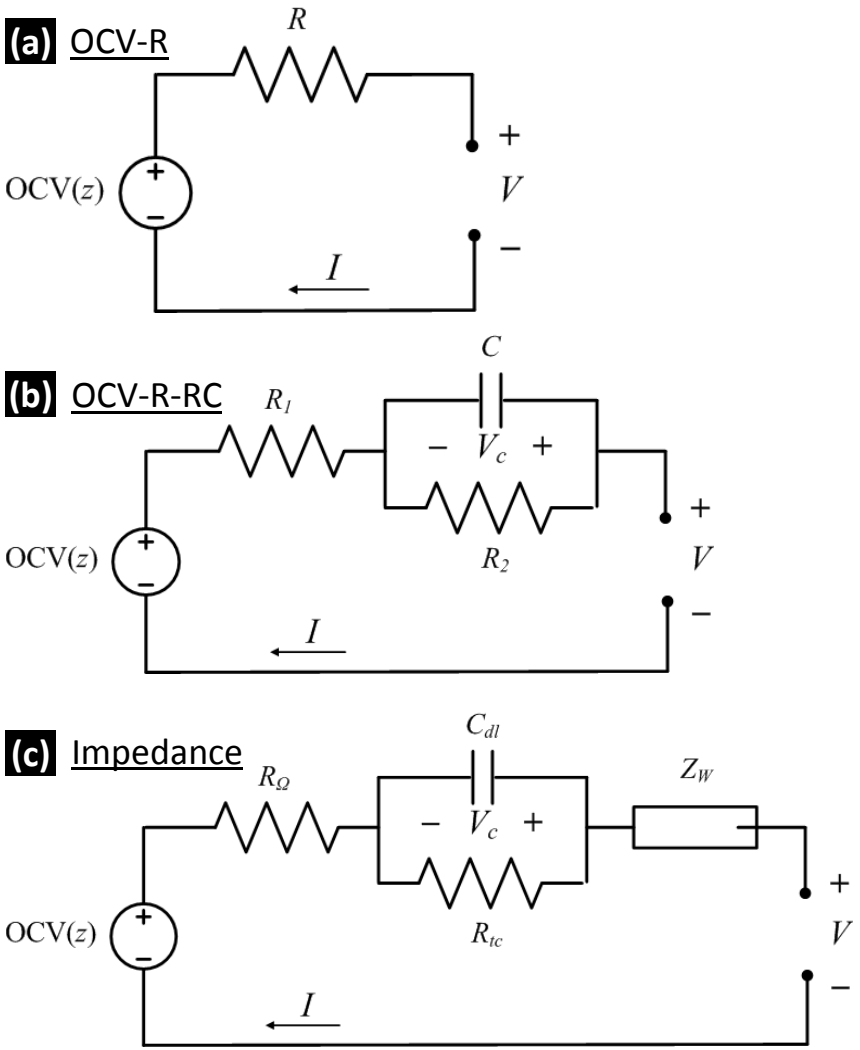


(c) Impedance

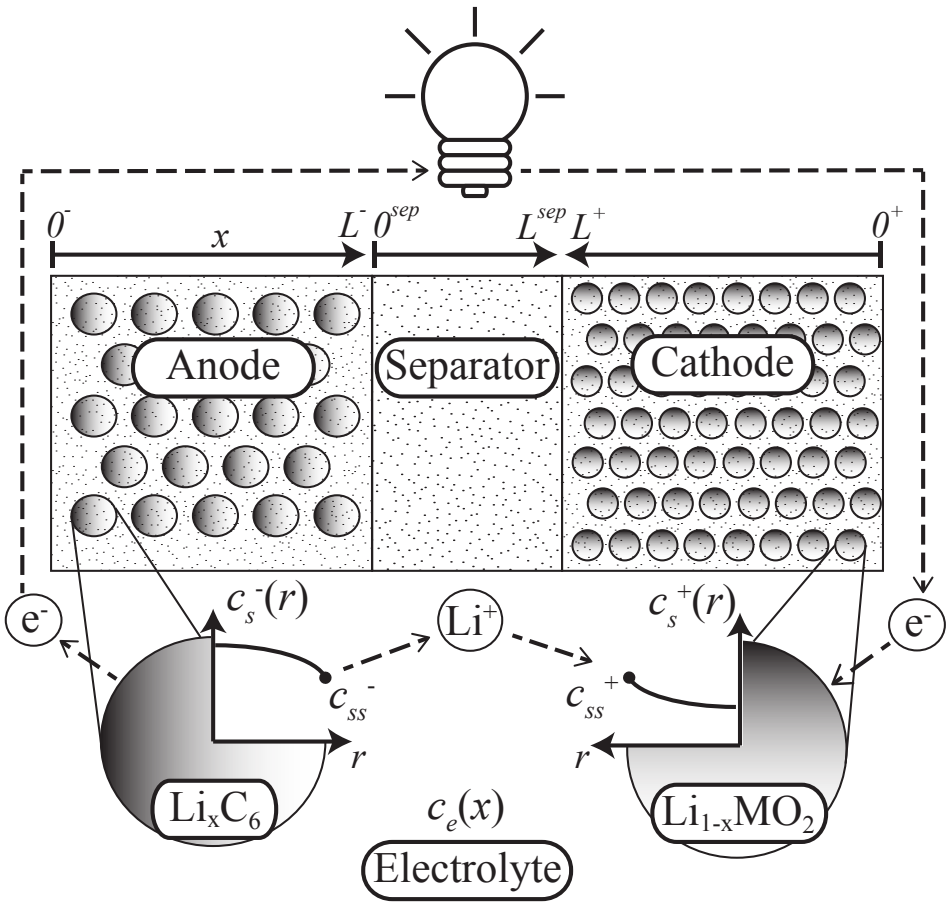


Battery Models

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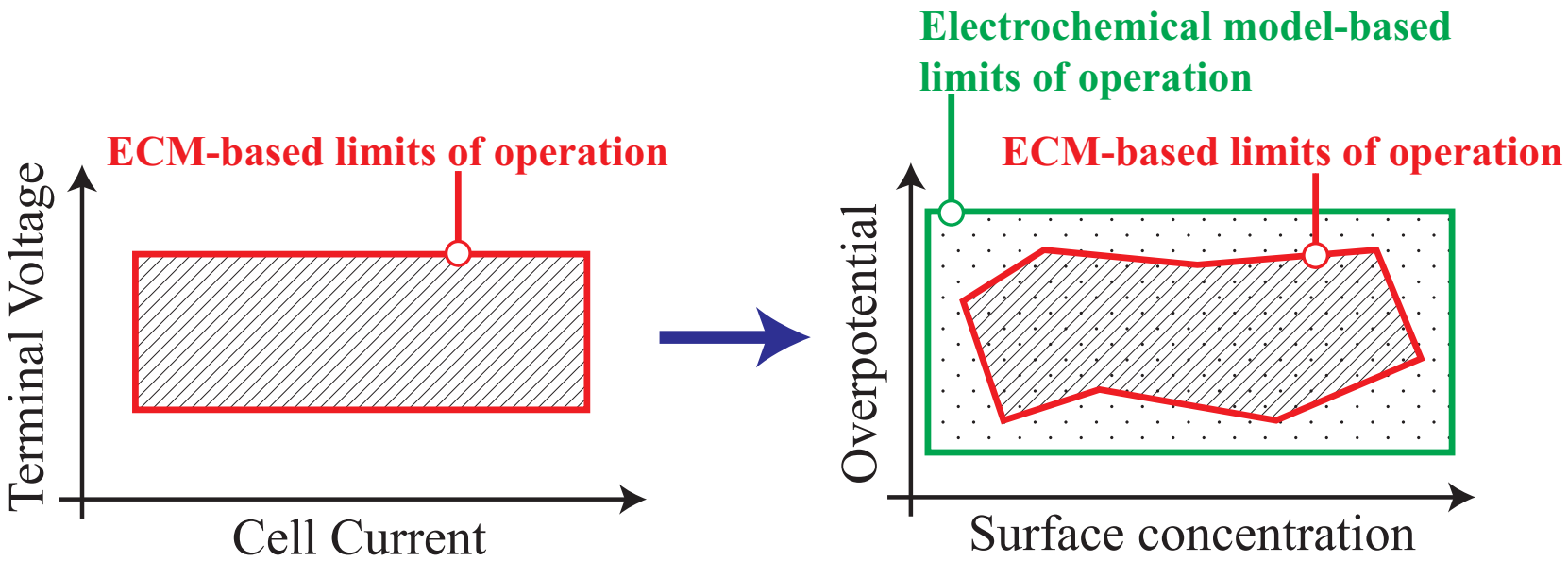


Electrochemical Model





Operate Batteries at their Physical Limits



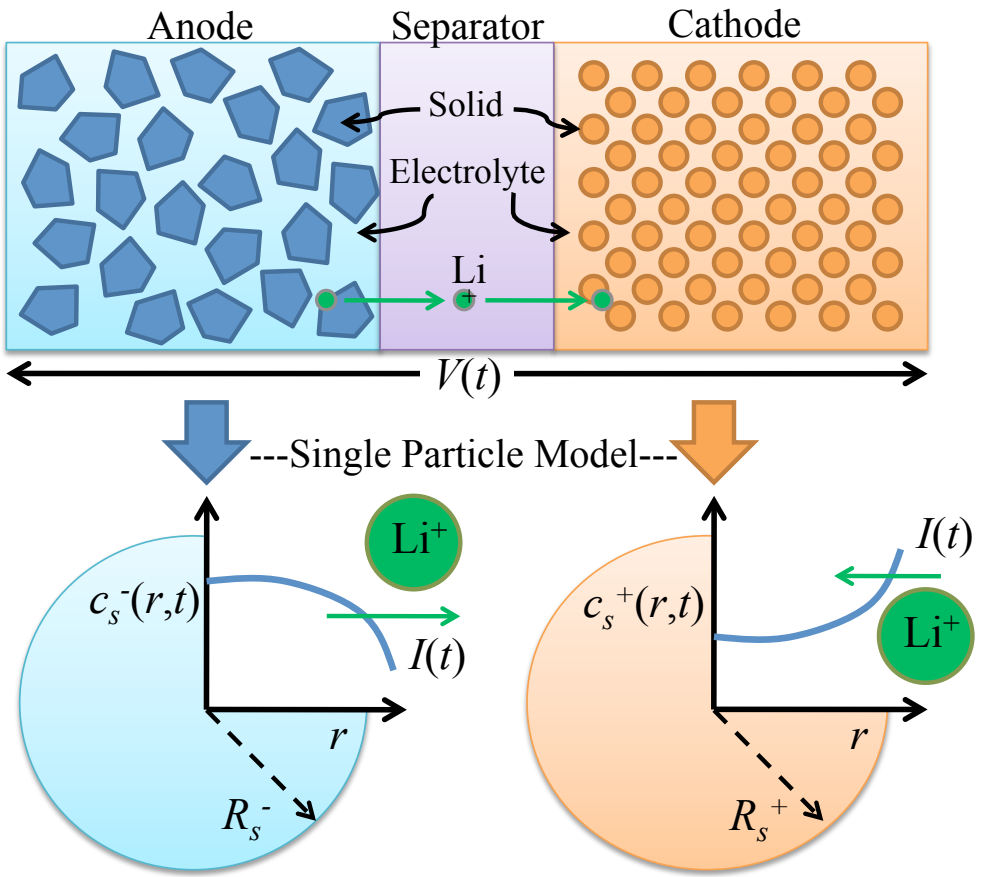
Electrochemical Model Equations

well, some of them

Description	**Equation**
Solid phase Li concentration	$\frac{\partial c_s^{\pm}}{\partial t}(x,r,t) = \frac{1}{r^2}\frac{\partial}{\partial r}\left[D_s^{\pm} r^2 \frac{\partial c_s^{\pm}}{\partial r}(x,r,t)\right]$
Electrolyte Li concentration	$\varepsilon_e \frac{\partial c_e}{\partial t}(x,t) = \frac{\partial}{\partial x}\left[\varepsilon_e D_e \frac{\partial c_e}{\partial x}(x,t) + \frac{1-t_c^0}{F} i_e^{\pm}(x,t)\right]$
Solid potential	$\frac{\partial \phi_s^{\pm}}{\partial x}(x,t) = \frac{i_e^{\pm}(x,t) - I(t)}{\sigma^{\pm}}$
Electrolyte potential	$\frac{\partial \phi_e}{\partial x}(x,t) = -\frac{i_e^{\pm}(x,t)}{\kappa} + \frac{2RT}{F}(1-t_c^0)\left(1 + \frac{d\ln f_{c/a}}{d\ln c_e}(x,t)\right)\frac{\partial \ln c_e}{\partial x}(x,t)$
Electrolyte ionic current	$\frac{\partial i_e^{\pm}}{\partial x}(x,t) = a_s F j_n^{\pm}(x,t)$
Molar flux btw phases	$j_n^{\pm}(x,t) = \frac{1}{F} i_0^{\pm}(x,t)\left[e^{\frac{\alpha_a F}{RT}\eta^{\pm}(x,t)} - e^{-\frac{\alpha_c F}{RT}\eta^{\pm}(x,t)}\right]$
Temperature	$\rho c_P \frac{dT}{dt}(t) = h\left[T^0(t) - T(t)\right] + I(t)V(t) - \int_{0^-}^{0^+} a_s F j_n(x,t)\Delta T(x,t)dx$

Animation of Li Ion Evolution

Single Particle Model (SPM)

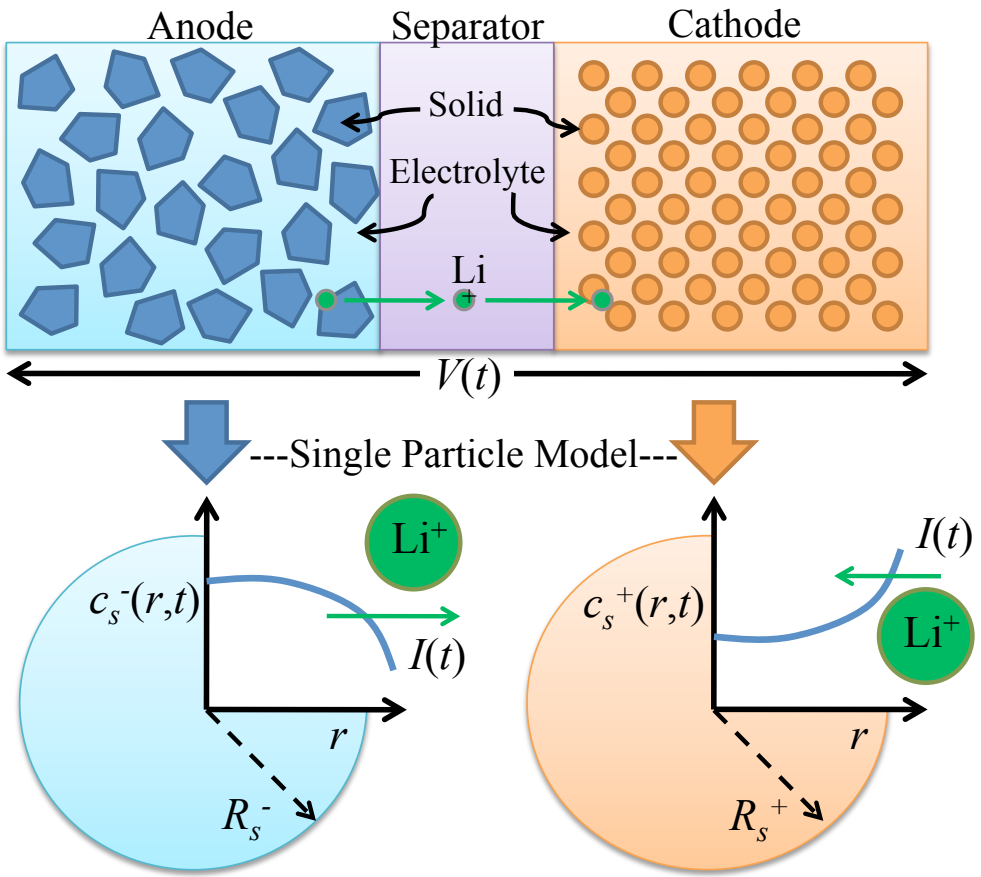


Single Particle Model (SPM)

Diffusion of Li in solid phase:

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

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



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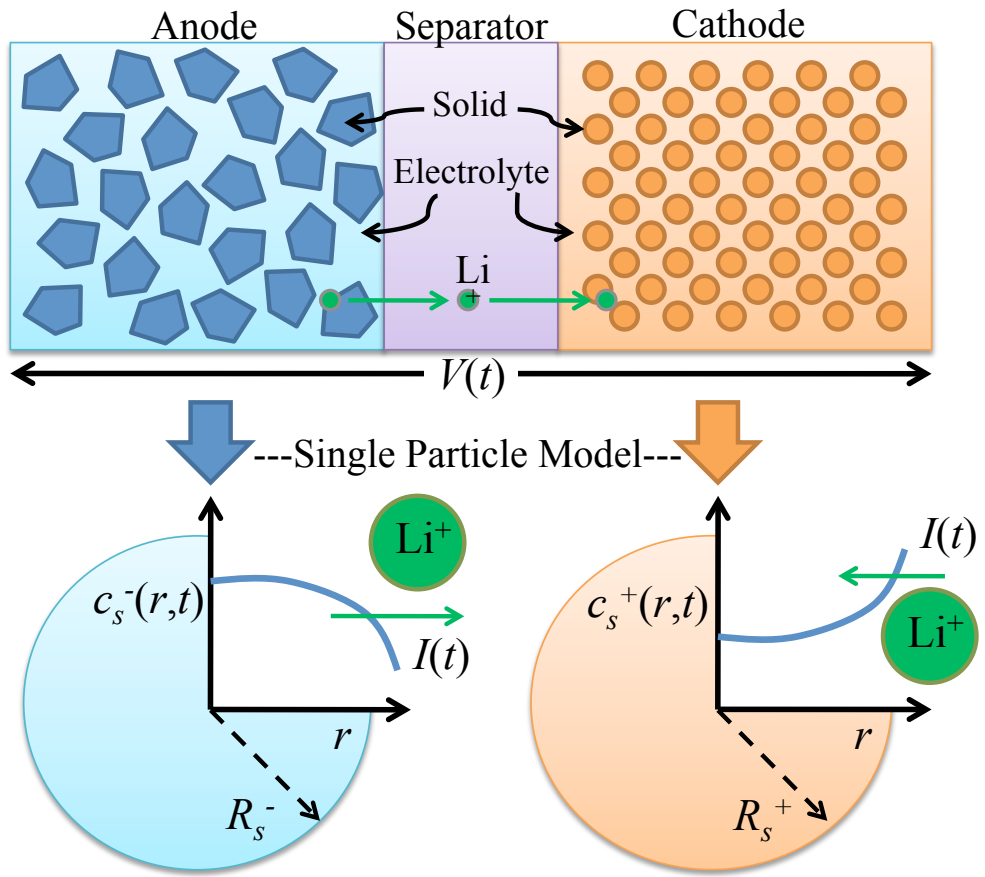
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Boundary conditions:

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

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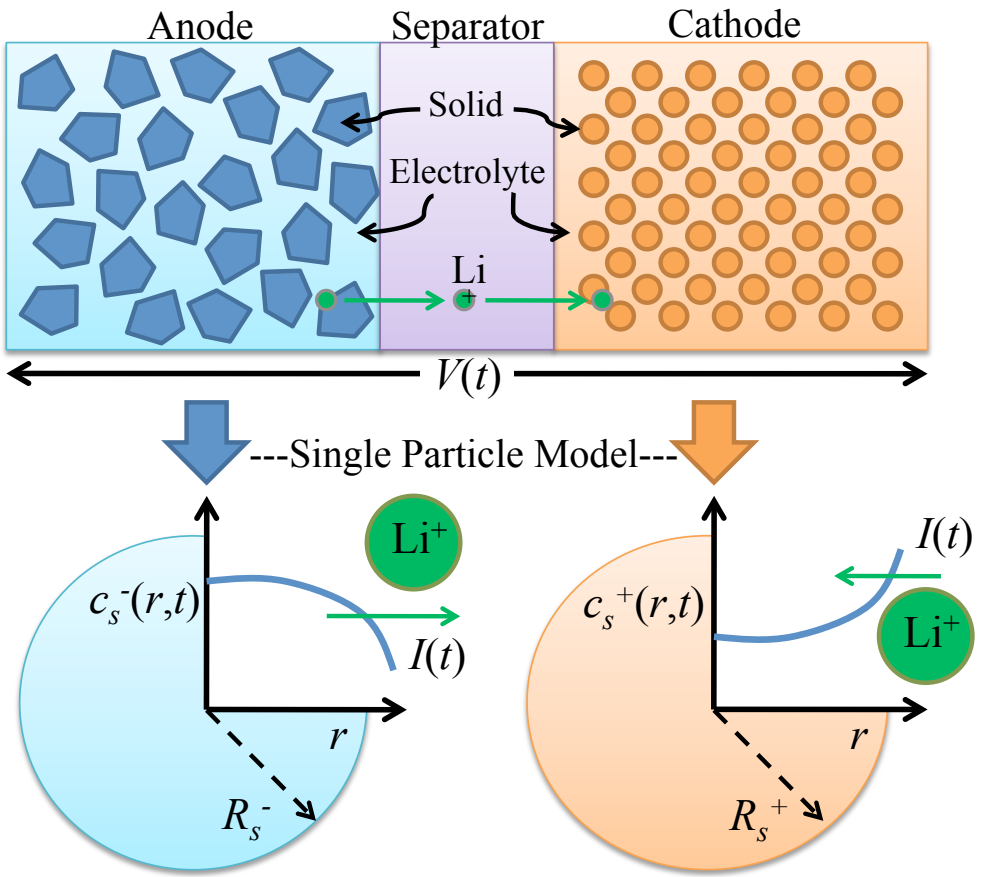
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Voltage Output Function:

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



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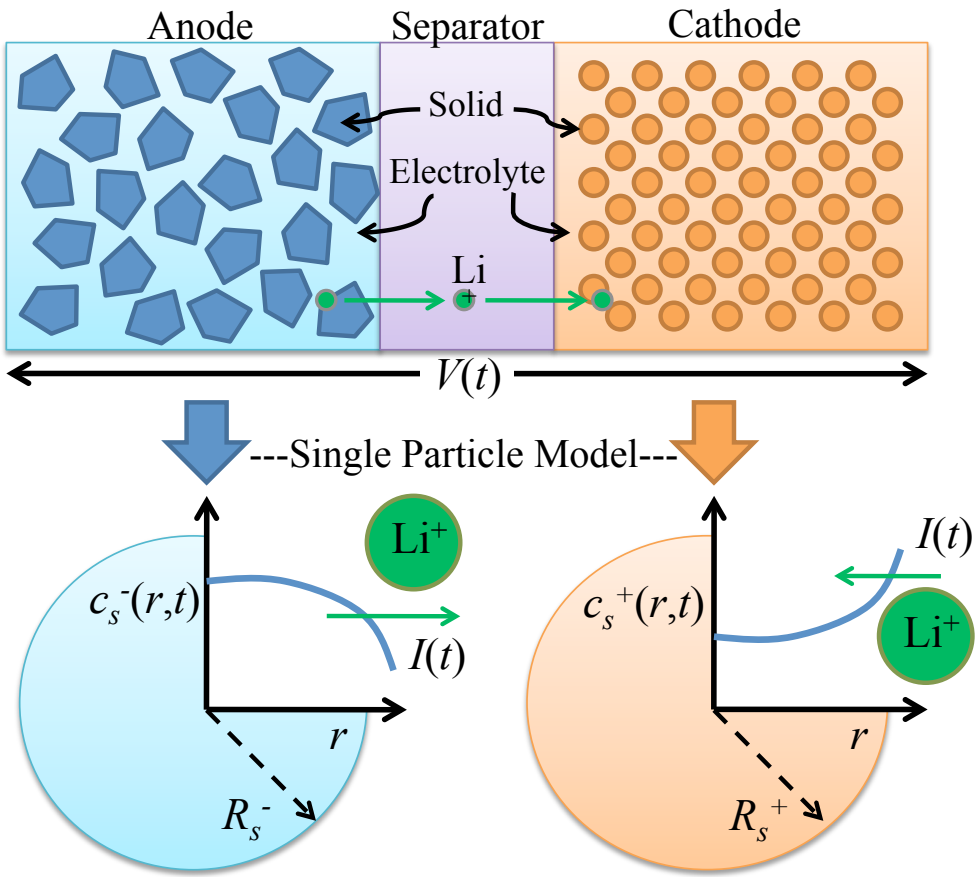
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Definitions

- 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

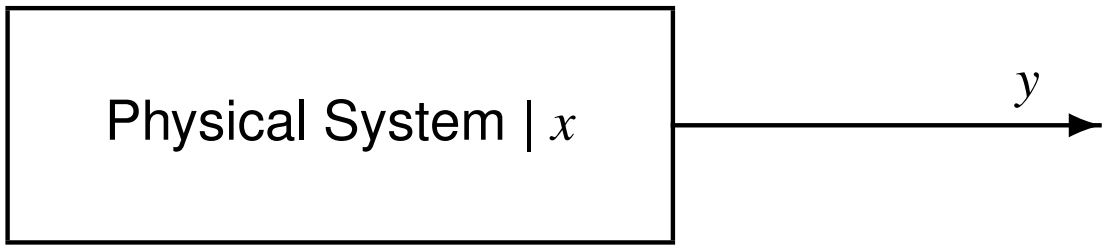
Estimate states $c_s^-(r,t), c_s^+(r,t)$ from measurements $I(t), V(t)$ and SPM

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Intro to Estimation

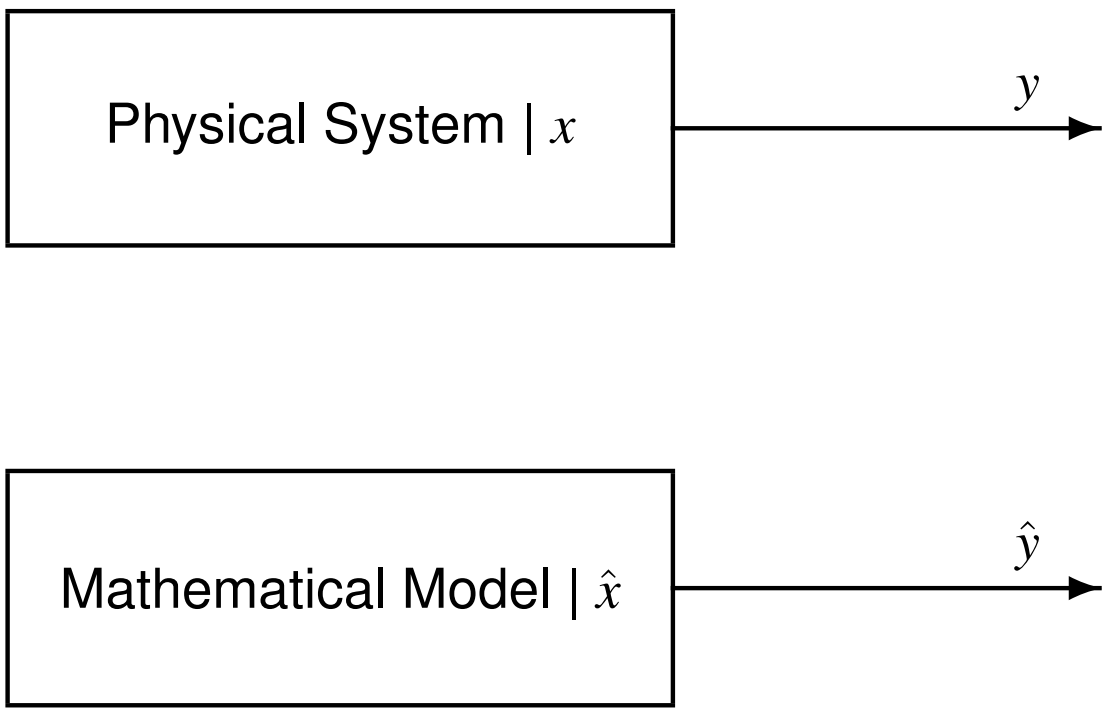


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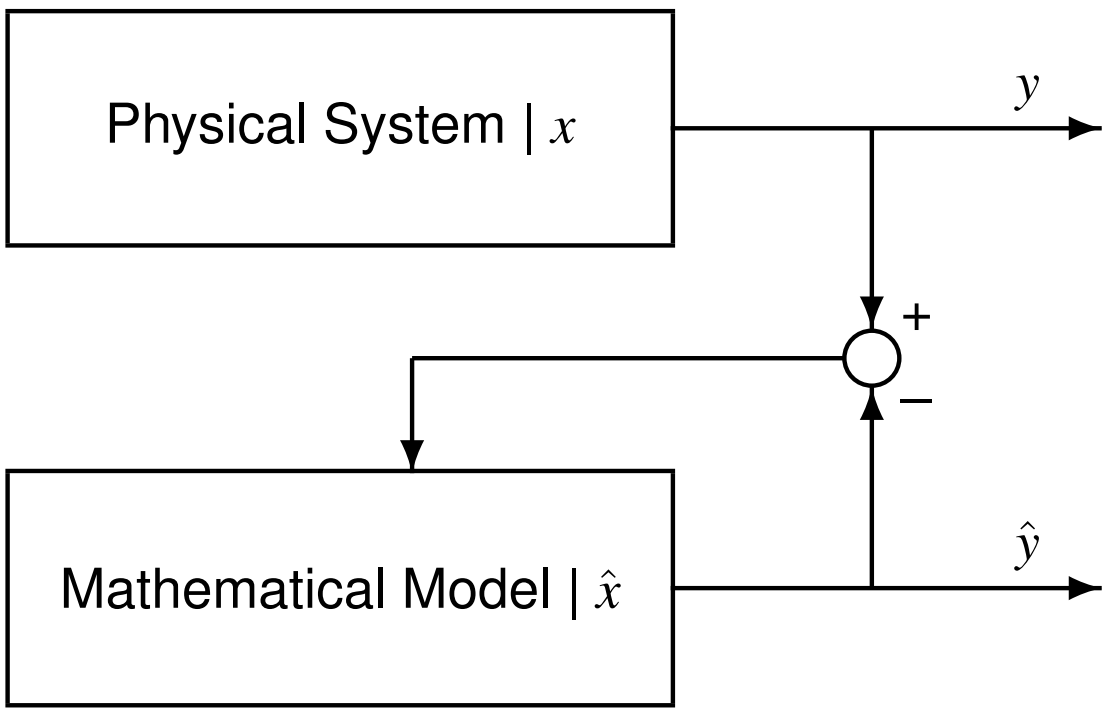


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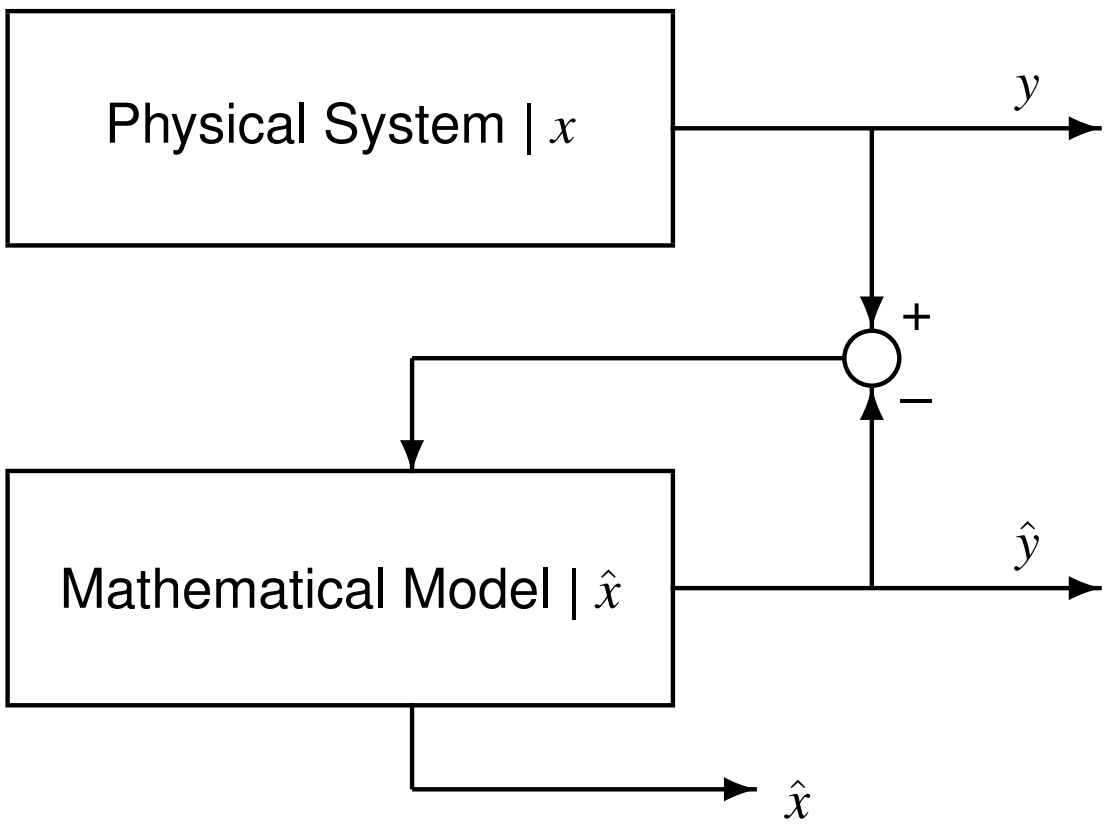


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Intro to Estimation



Backstepping PDE Estimator

Simplify the Math

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

Backstepping PDE Estimator

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

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

Backstepping PDE Estimator

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

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

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\end{aligned}$$

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

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

Backstepping PDE Estimator

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\end{aligned}$$

The Concept

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

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

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

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

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

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

Backstepping PDE Estimator

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

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\end{aligned}$$

Kernel PDE

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

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

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

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

Backstepping PDE Estimator

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\end{aligned}$$

Explicit Solution to Estimator Gains

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

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

The SOH Estimation Problem

Problem Statement

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

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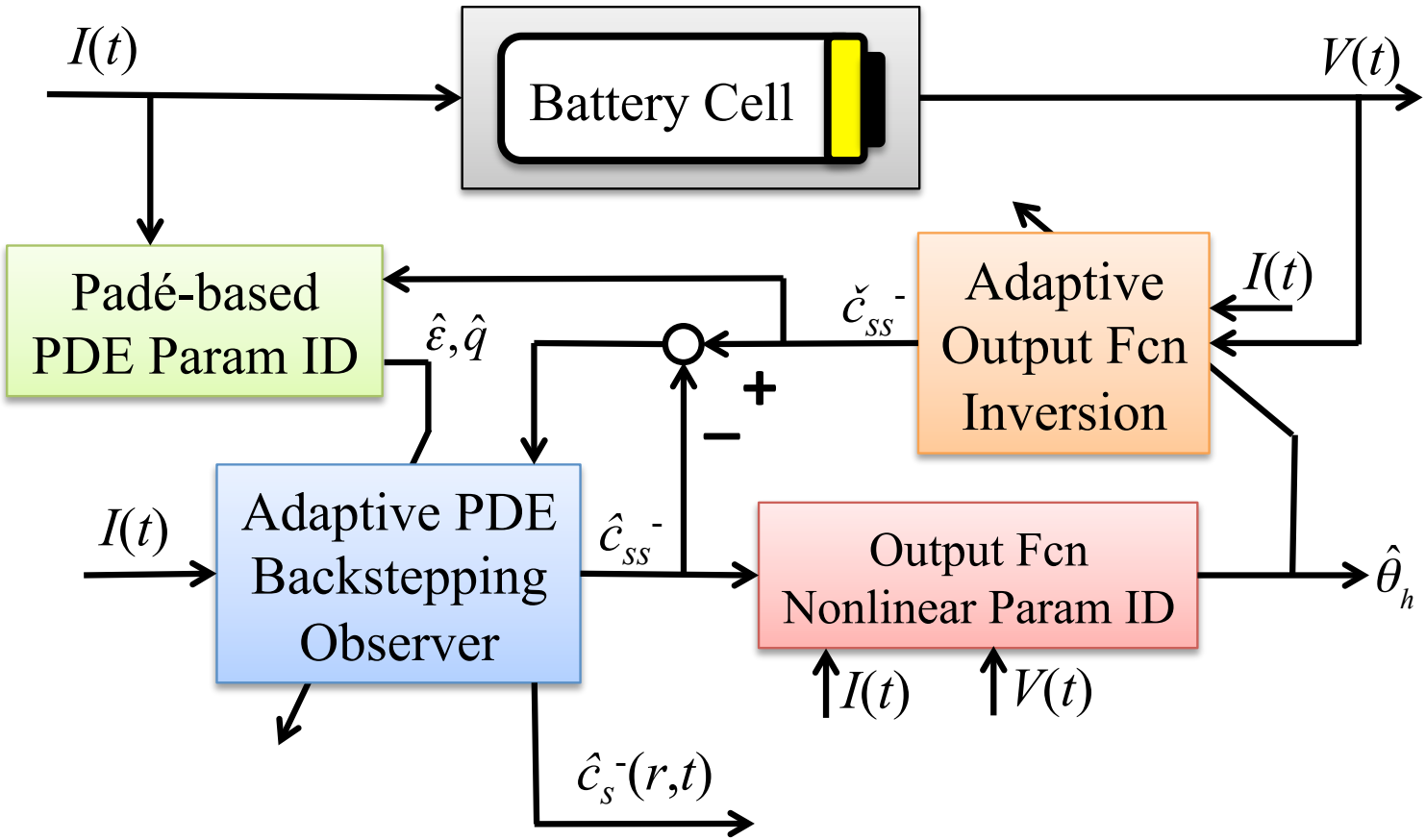
Estimate physical parameters from measurements $I(t), V(t)$ and SPM

Relate uncertain parameters to SOH-related concepts

- Capacity fade
- Power fade

Adaptive Observer

Combined State & Parameter Estimation



Output Function Nonlinear Parameter ID

Nonlinearly Parameterized Output

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

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

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Identifiability Analysis

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

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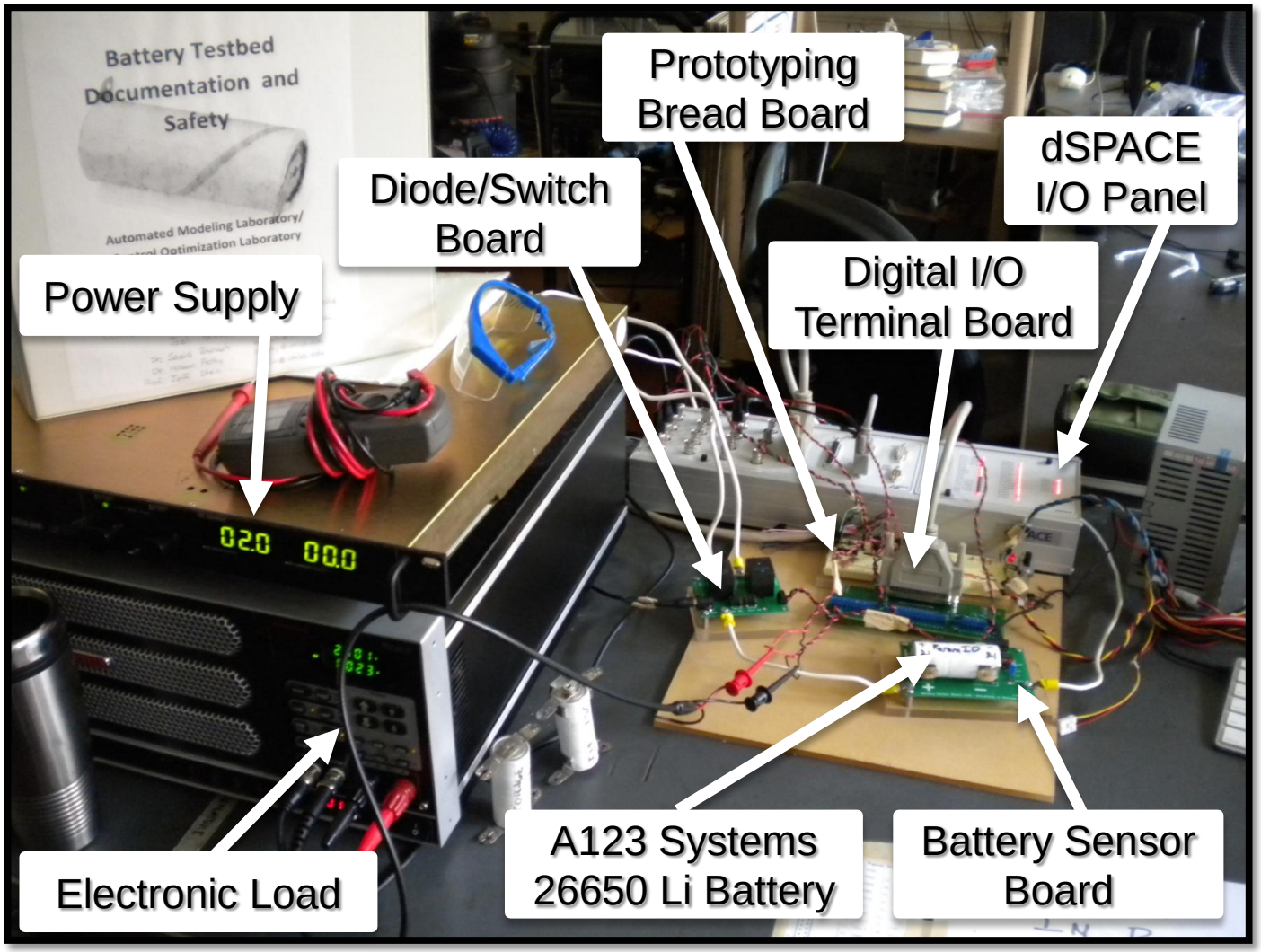
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  - n_{Li} : Moles of cyclable Li (Capacity Fade)
  - R_f : Resistance of current collectors, electrolyte, etc. (Power Fade)

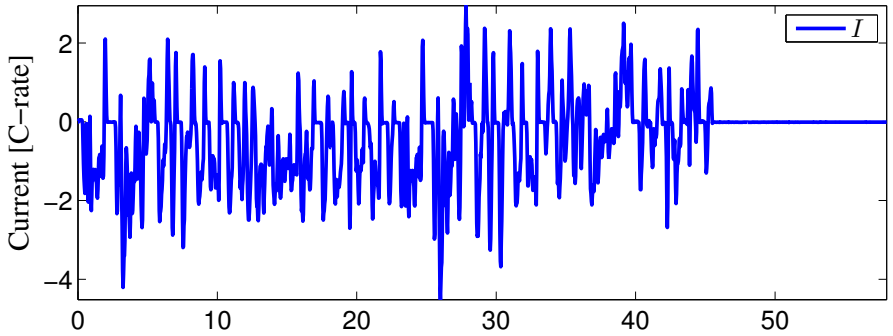
Apply nonlinear recursive least squares to θ_h

Custom-Built Battery-in-the-Loop Testbed



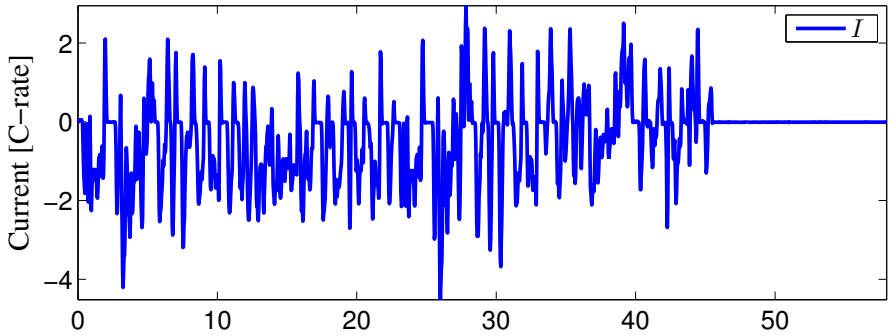
Results

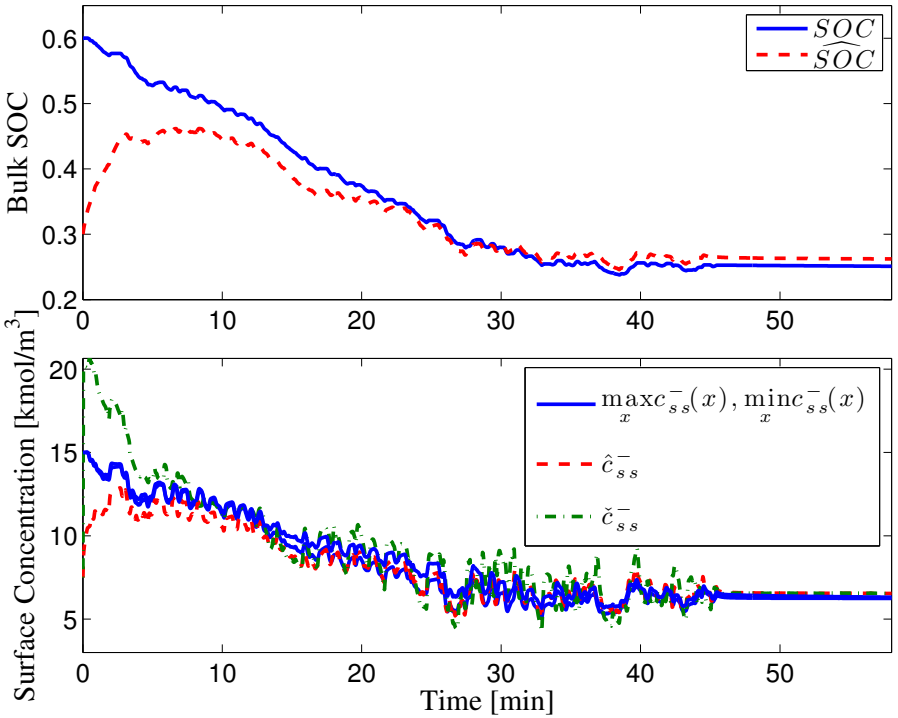
UDDS Drive Cycle Input



Results

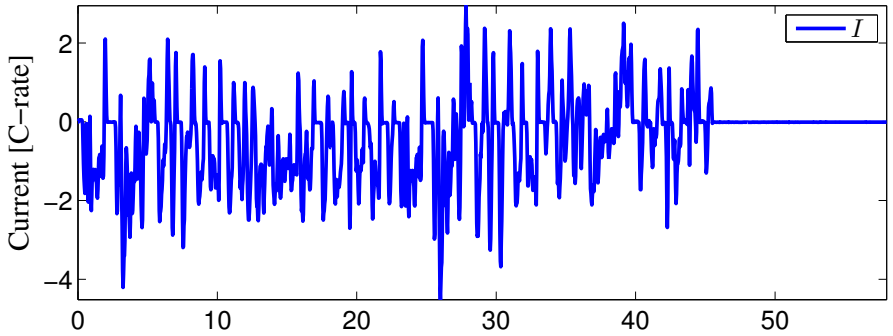
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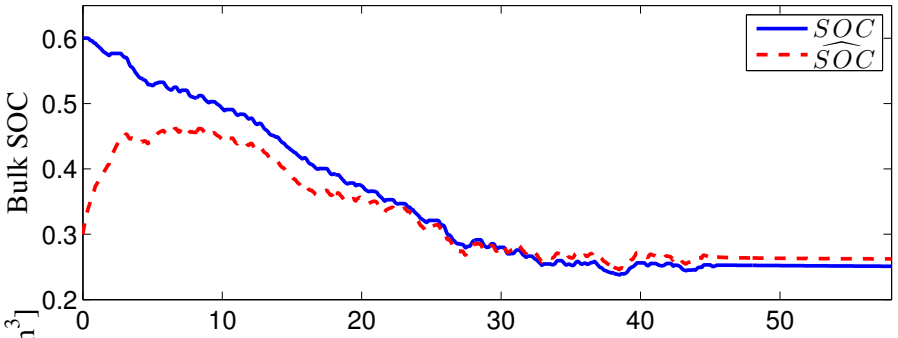


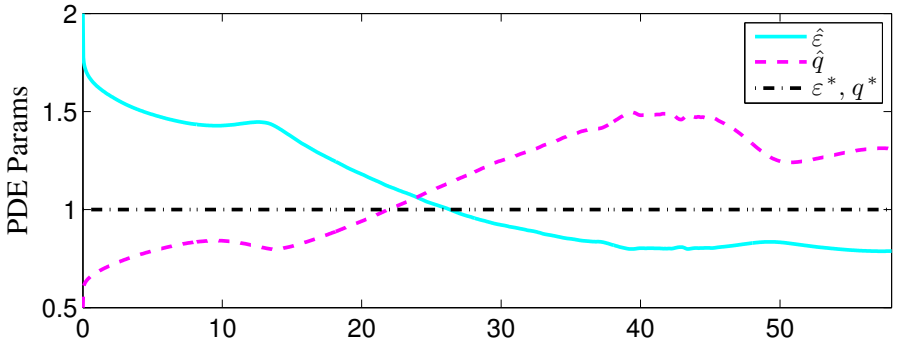


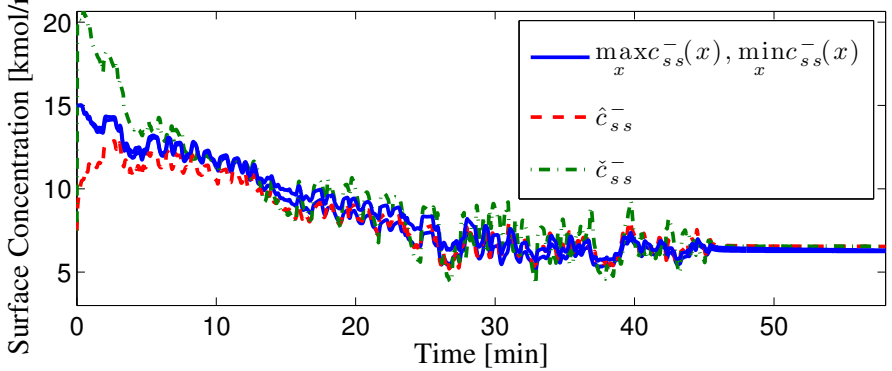
Results

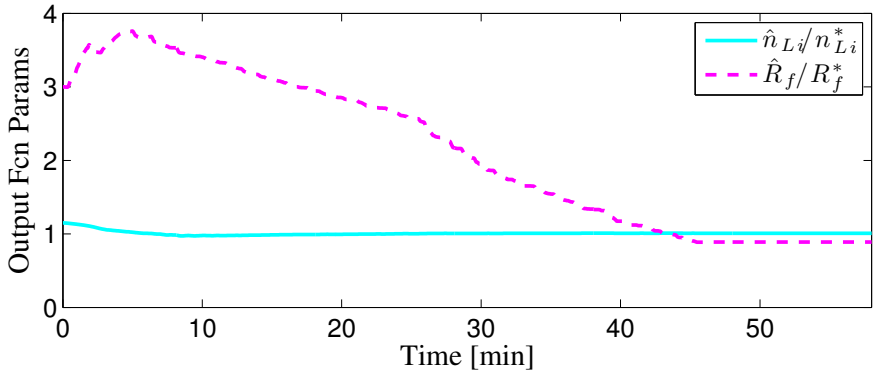
UDDS Drive Cycle Input





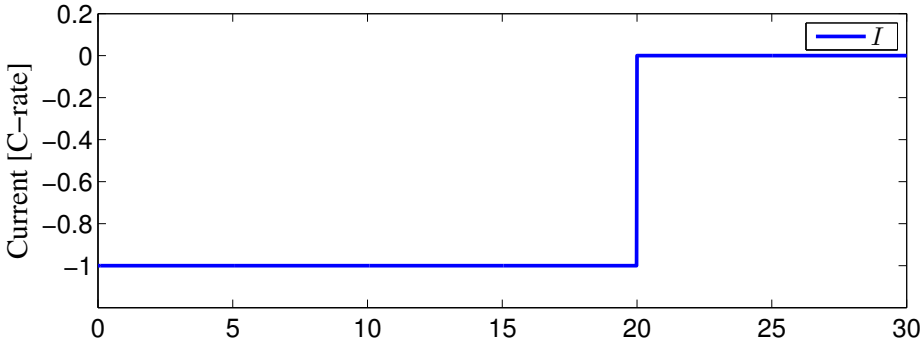


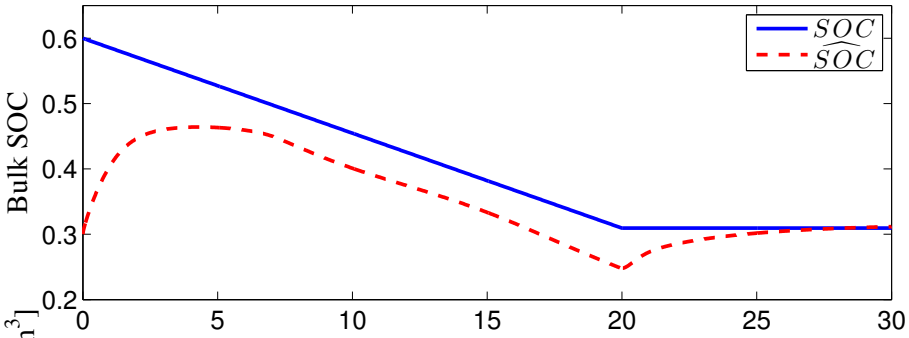


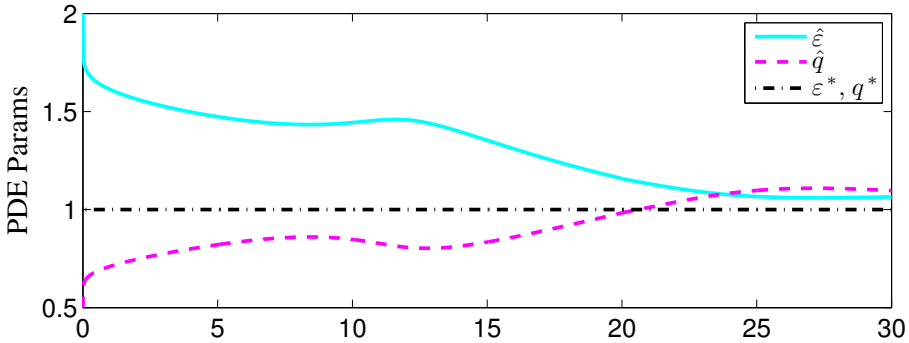


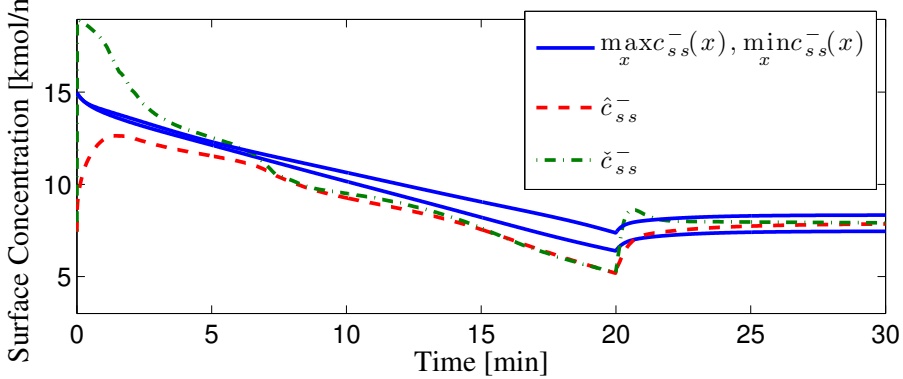
Results

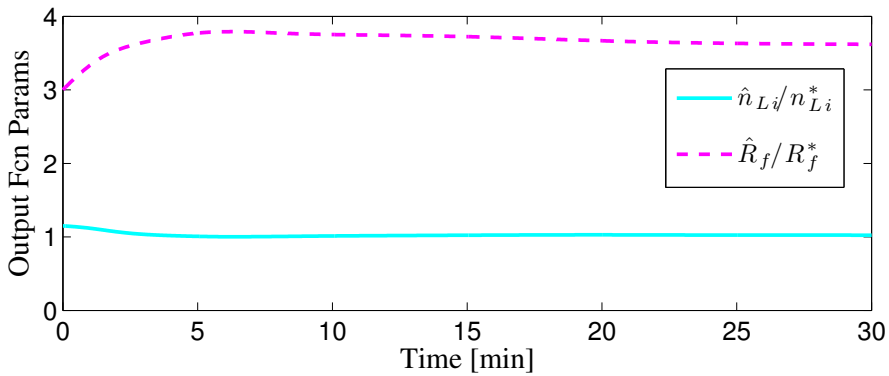
Constant 1C Discharge





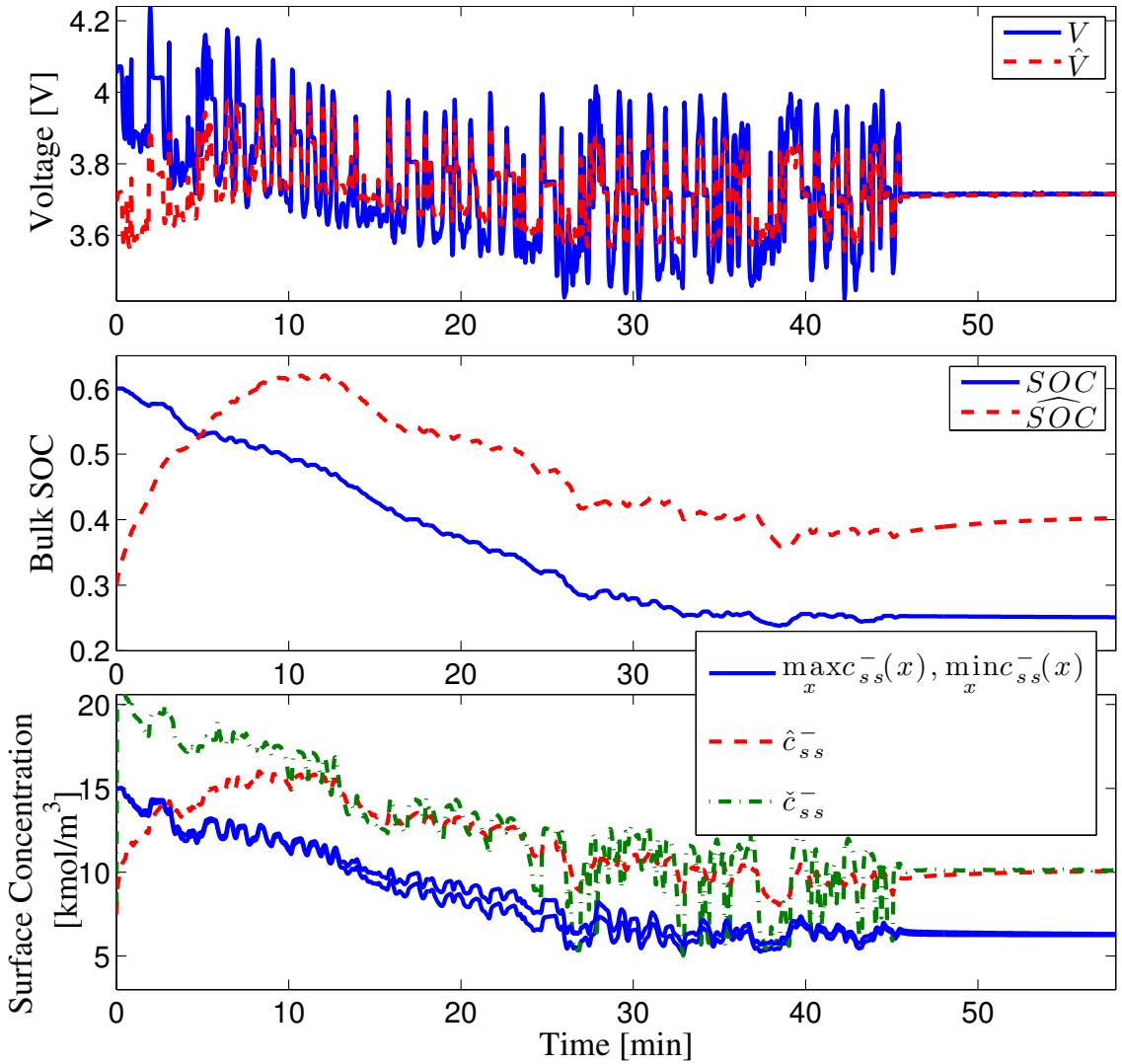






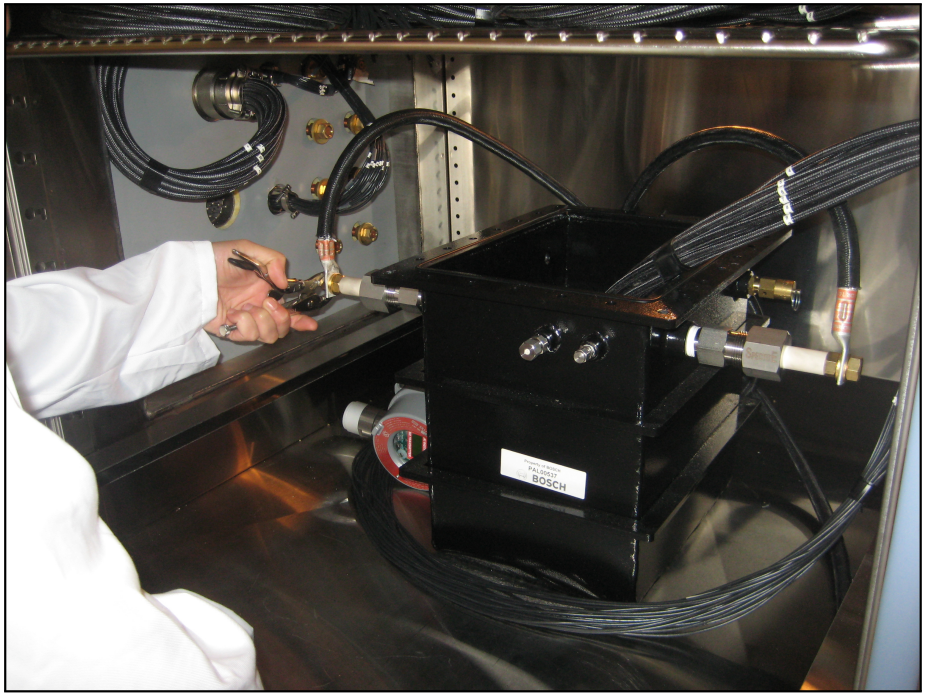
Results

No Parameter Adaption - Bias in State Estimates



Experimental Testing | ARPA-E AMPED Program





Outline

1. Batteries
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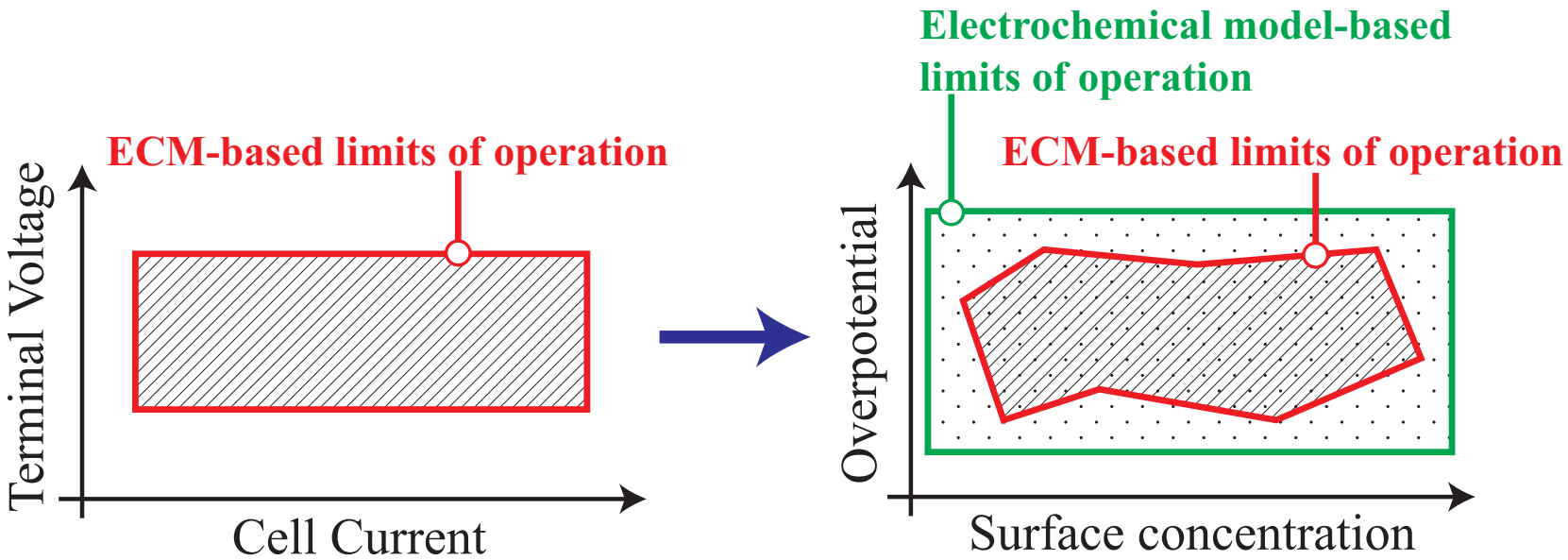
Operate Batteries at their Physical Limits



Operate Batteries at their Physical Limits

Problem Statement

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

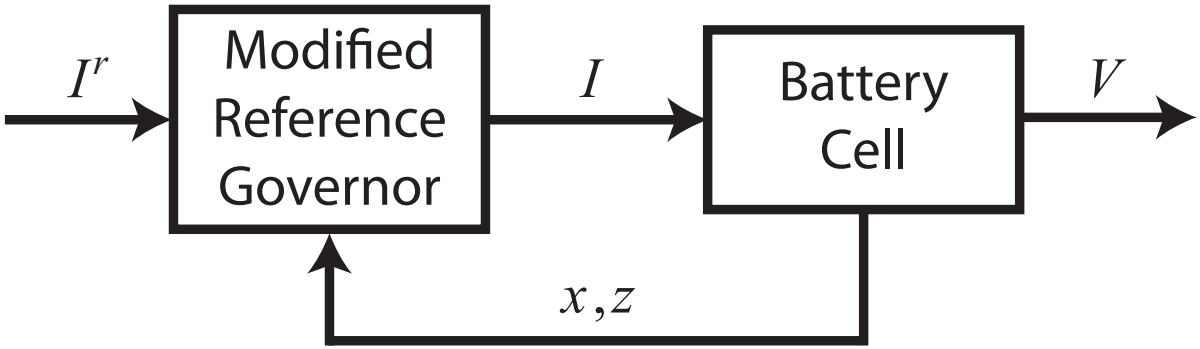


Constraints

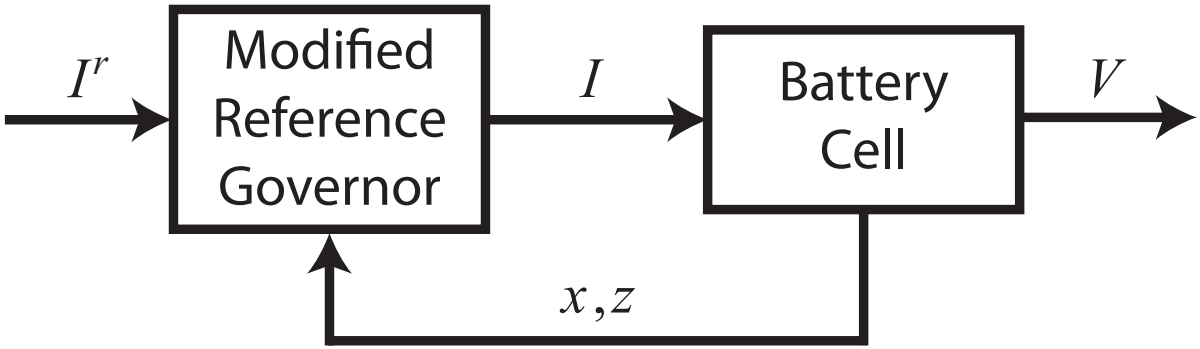
Variable	Definition	Constraint
$I(t)$	Current	Power electronics limits
$c_s^{\pm}(x,r,t)$	Li concentration in solid	Saturation/depletion
$\frac{\partial c_s^{\pm}}{\partial r}(x,r,t)$	Li concentration gradient	Diffusion-induced stress
$c_e(x,t)$	Li concentration in electrolyte	Saturation/depletion
$T(t)$	Temperature	High/low temps accel. aging
$\eta_s(x,t)$	Side-rxn overpotential	Li plating, dendrite formation

Each variable, y, must satisfy $y_{\min} \leq y \leq y_{\max}$.

The Algorithm: Modified Reference Governor (MRG)



The Algorithm: Modified Reference Governor (MRG)

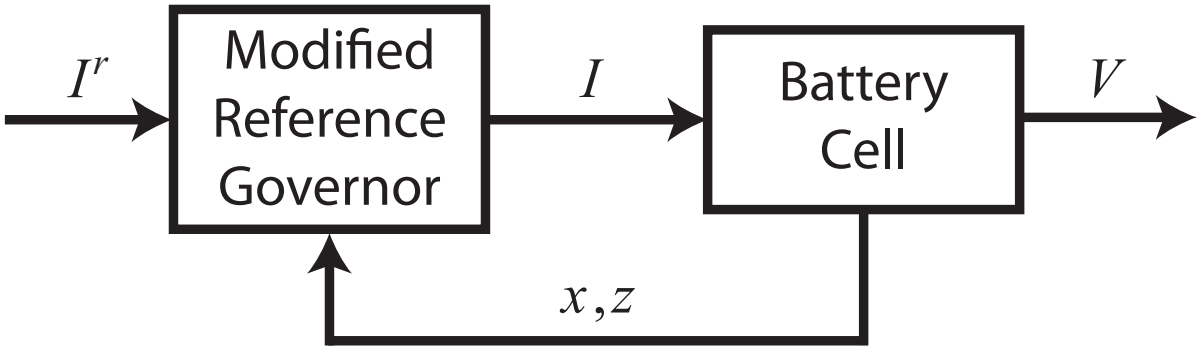


MRG Equations

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

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

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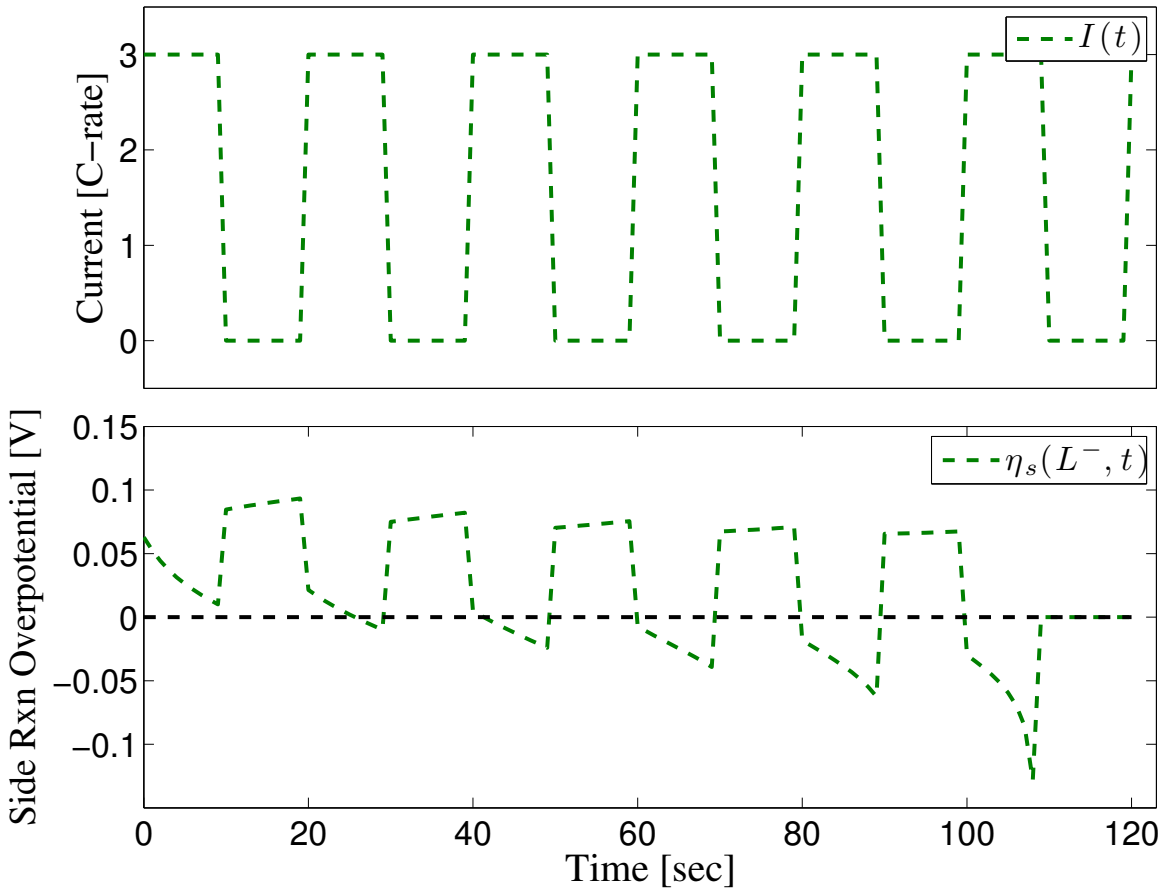
$$\beta^*[k] = \max\{\beta \in [0,1] : (x(t), z(t)) \in \mathcal{O}\}$$

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

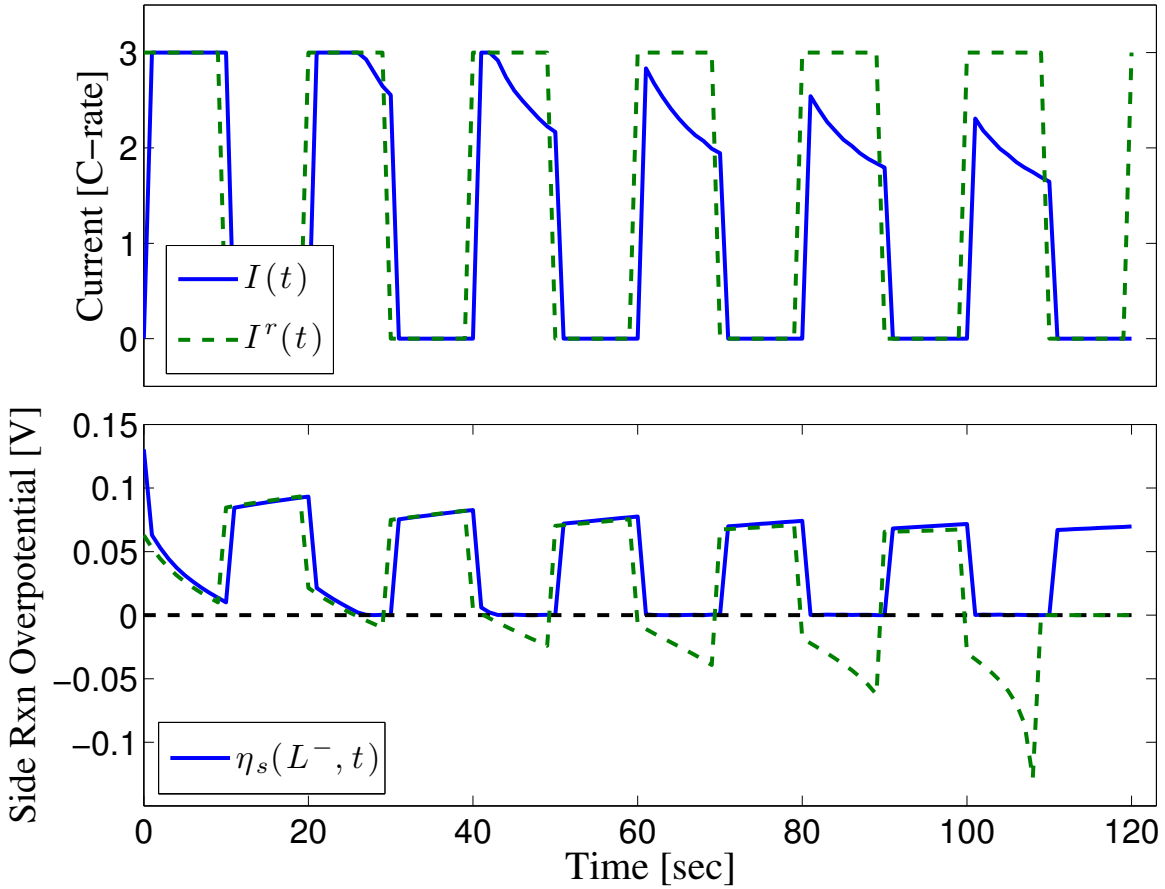
$$\mathcal{O} = \{(x(t), z(t)) : y(\tau) \in \mathcal{Y}, \forall \tau \in [t, t+T_s]\}$$

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

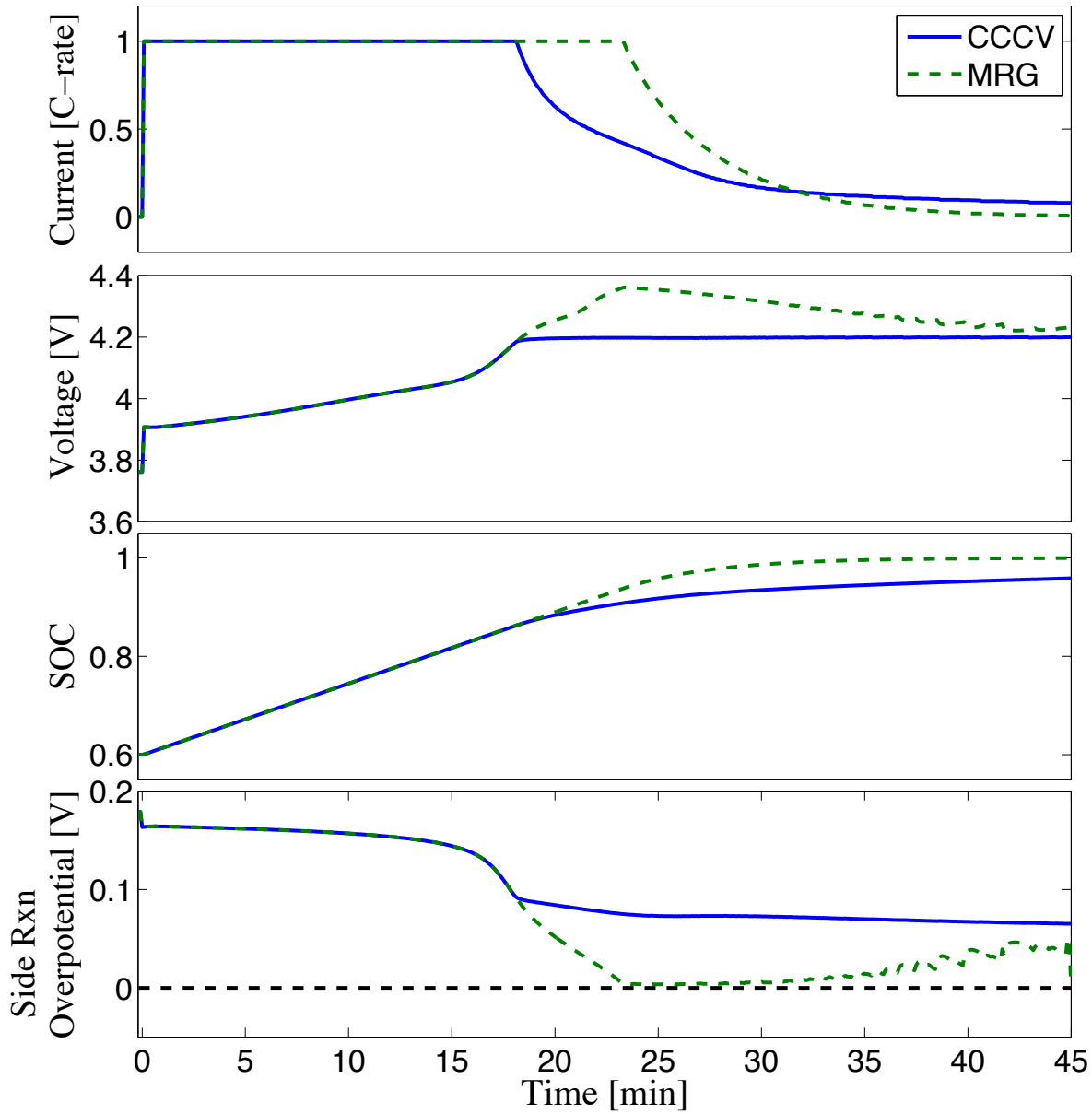
Constrained Control of EChem States



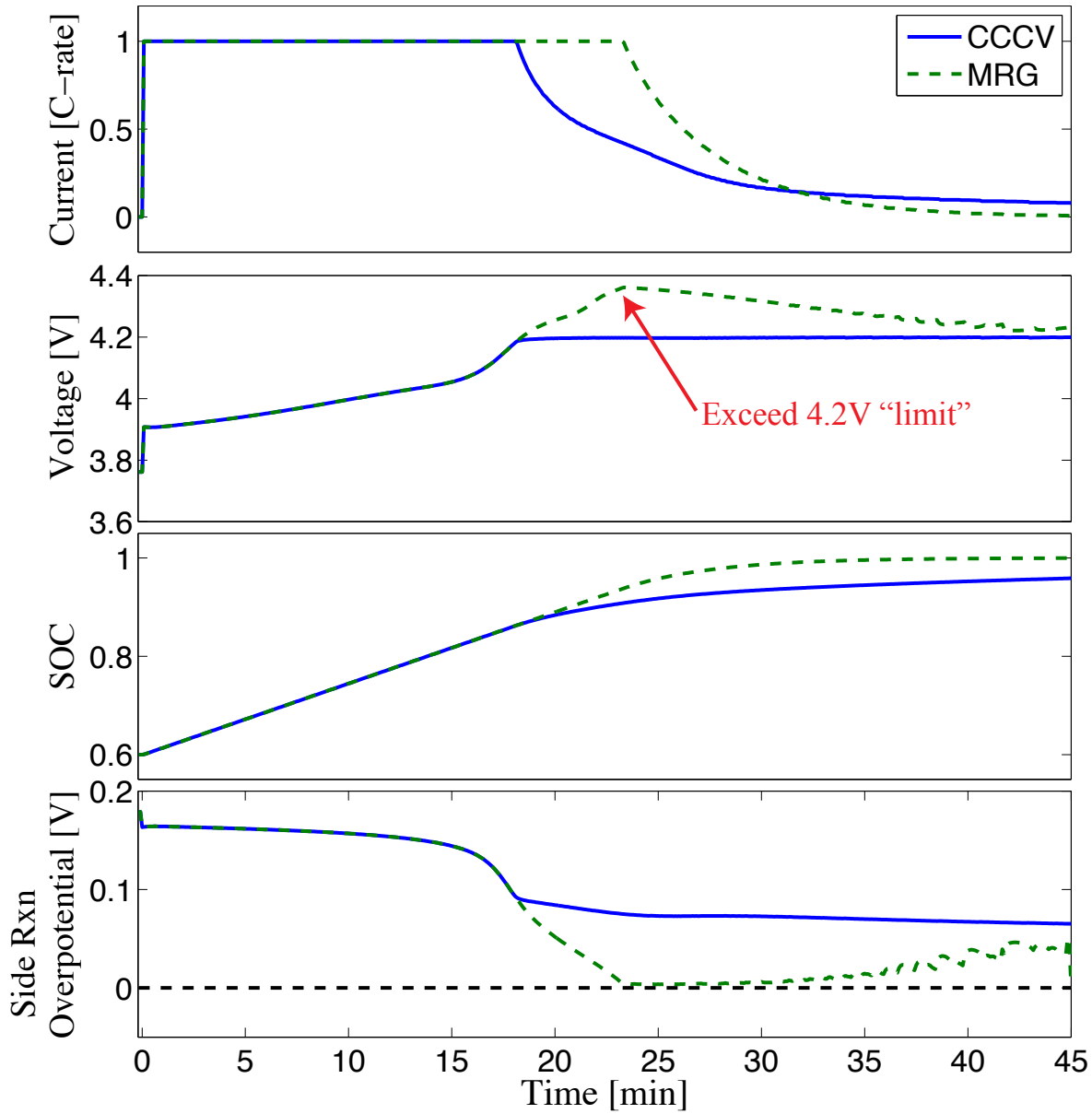
Constrained Control of EChem States



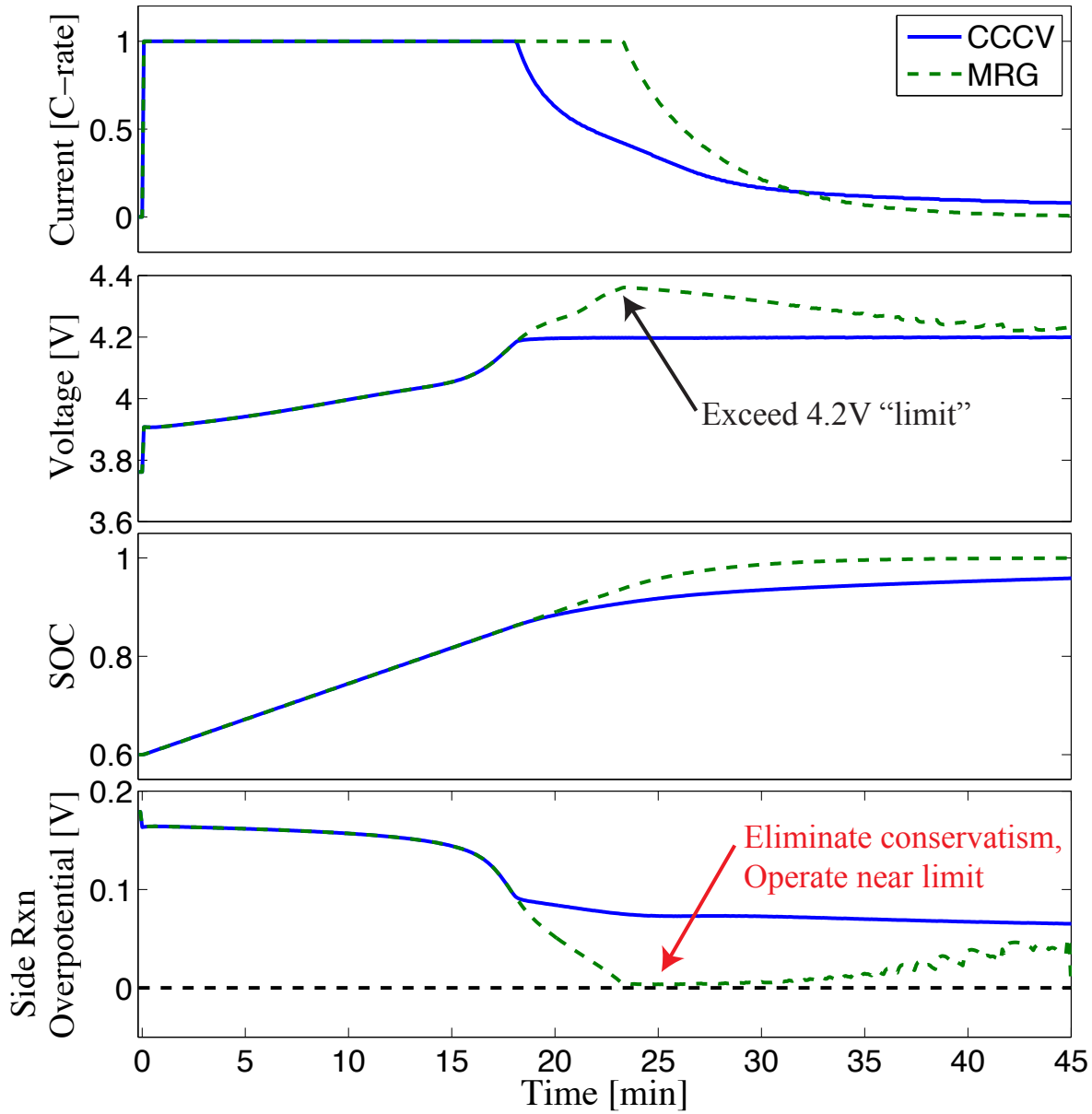
Application to Charging



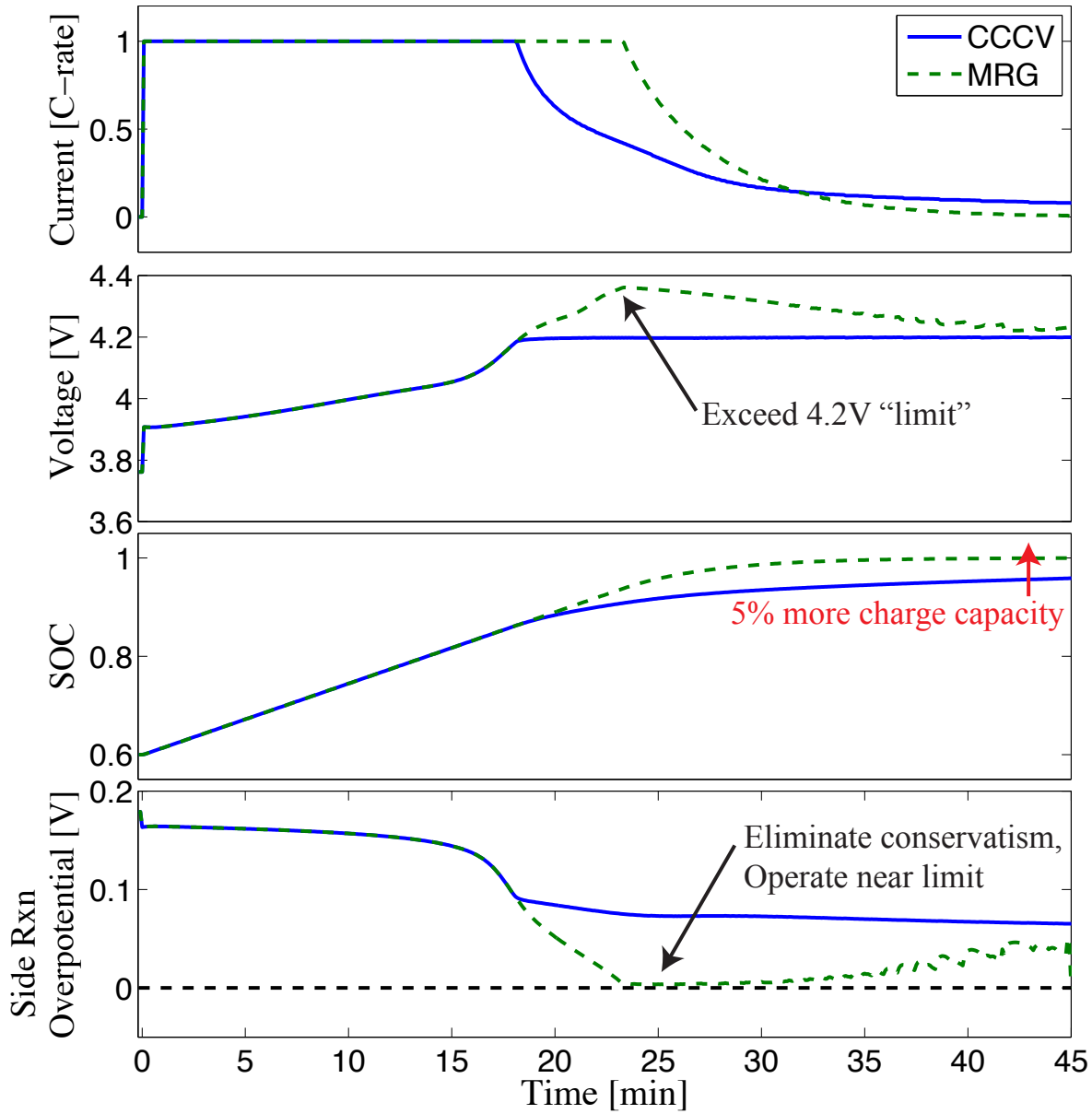
Application to Charging



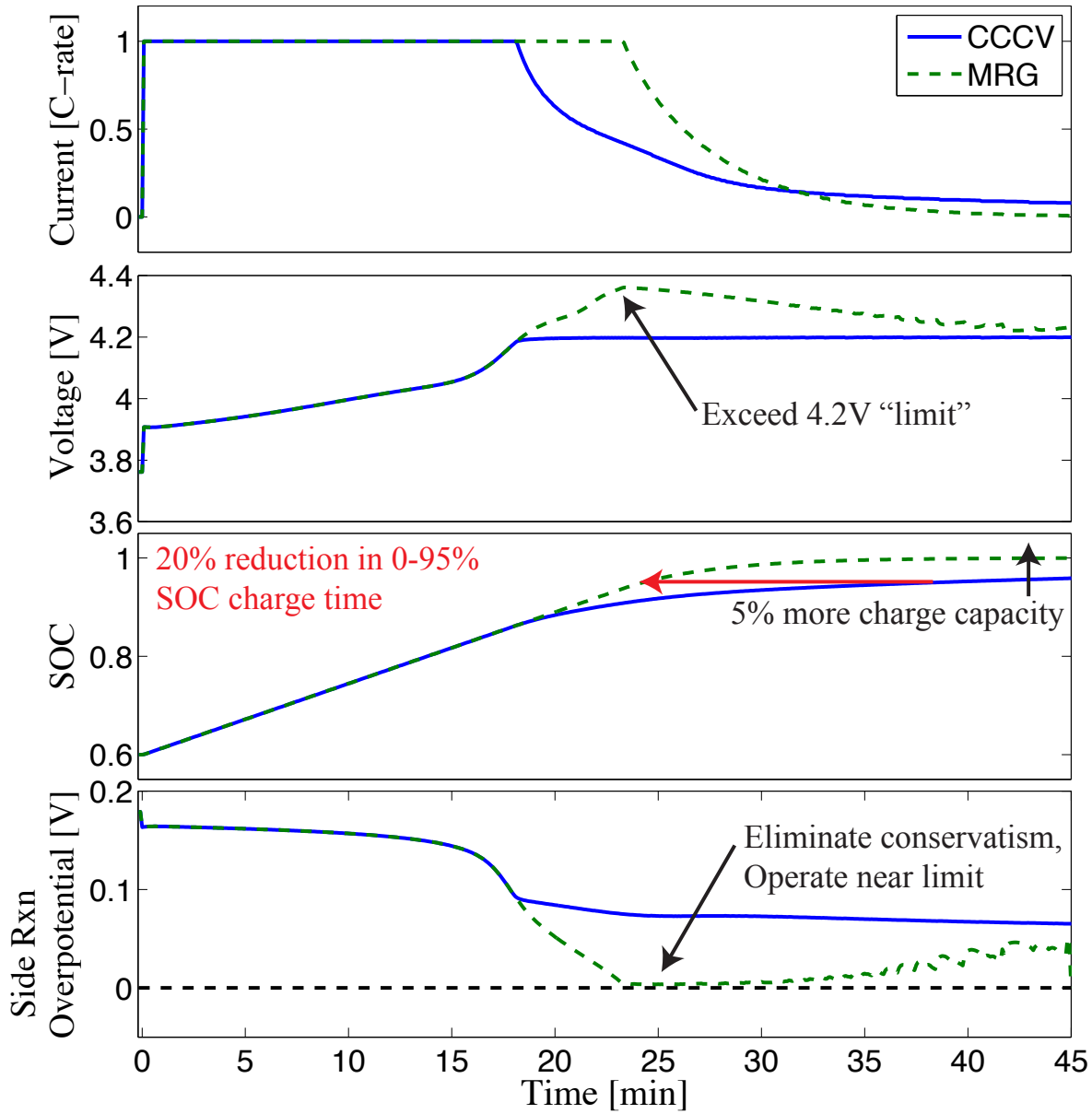
Application to Charging



Application to Charging



Application to Charging



Outline

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   - [Electrochemical Modeling] Incorporating Physics
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PHEV Power Management

Problem Statement

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



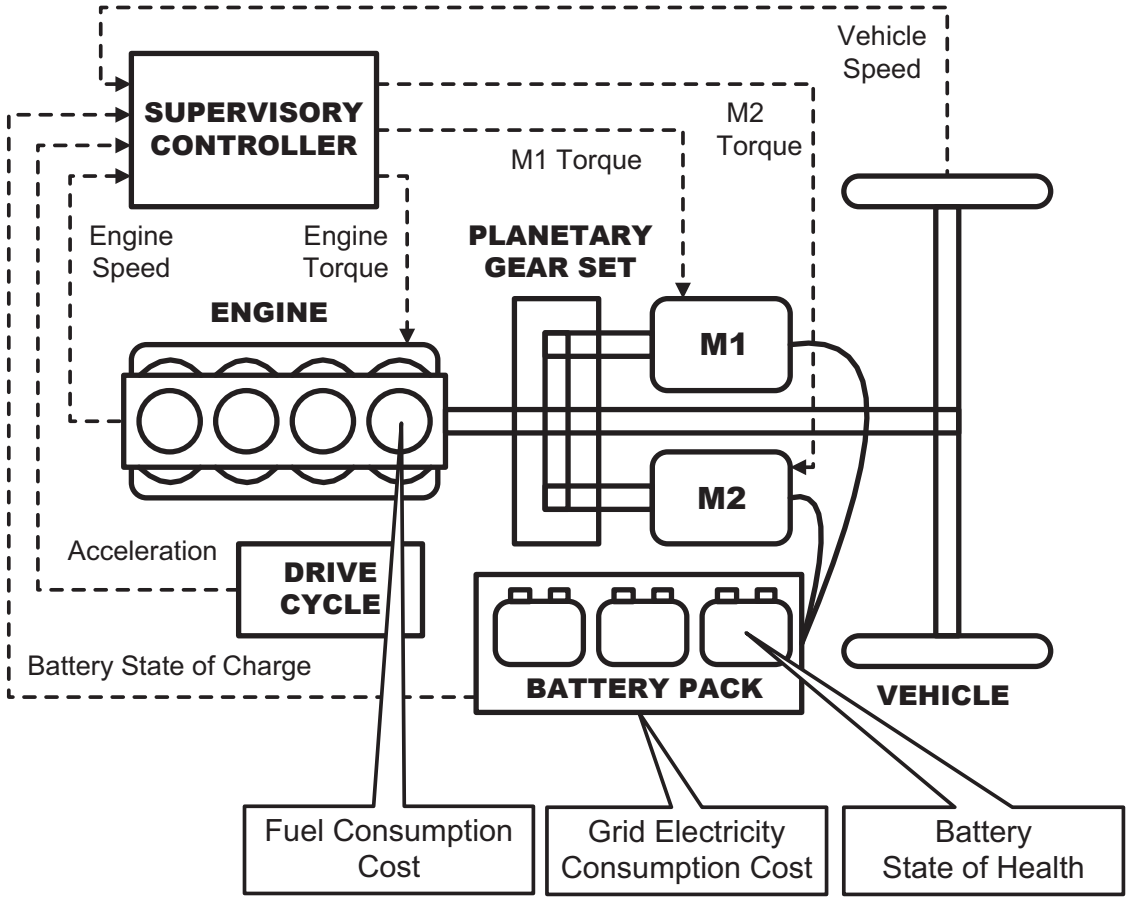
J. Voelcker, "Plugging Away in a Prius," *IEEE Spectrum*, vol. 45, pp. 30-48, 2008.



Power-Split PHEV Model

Ex: Toyota Prius, Ford Escape Hybrid

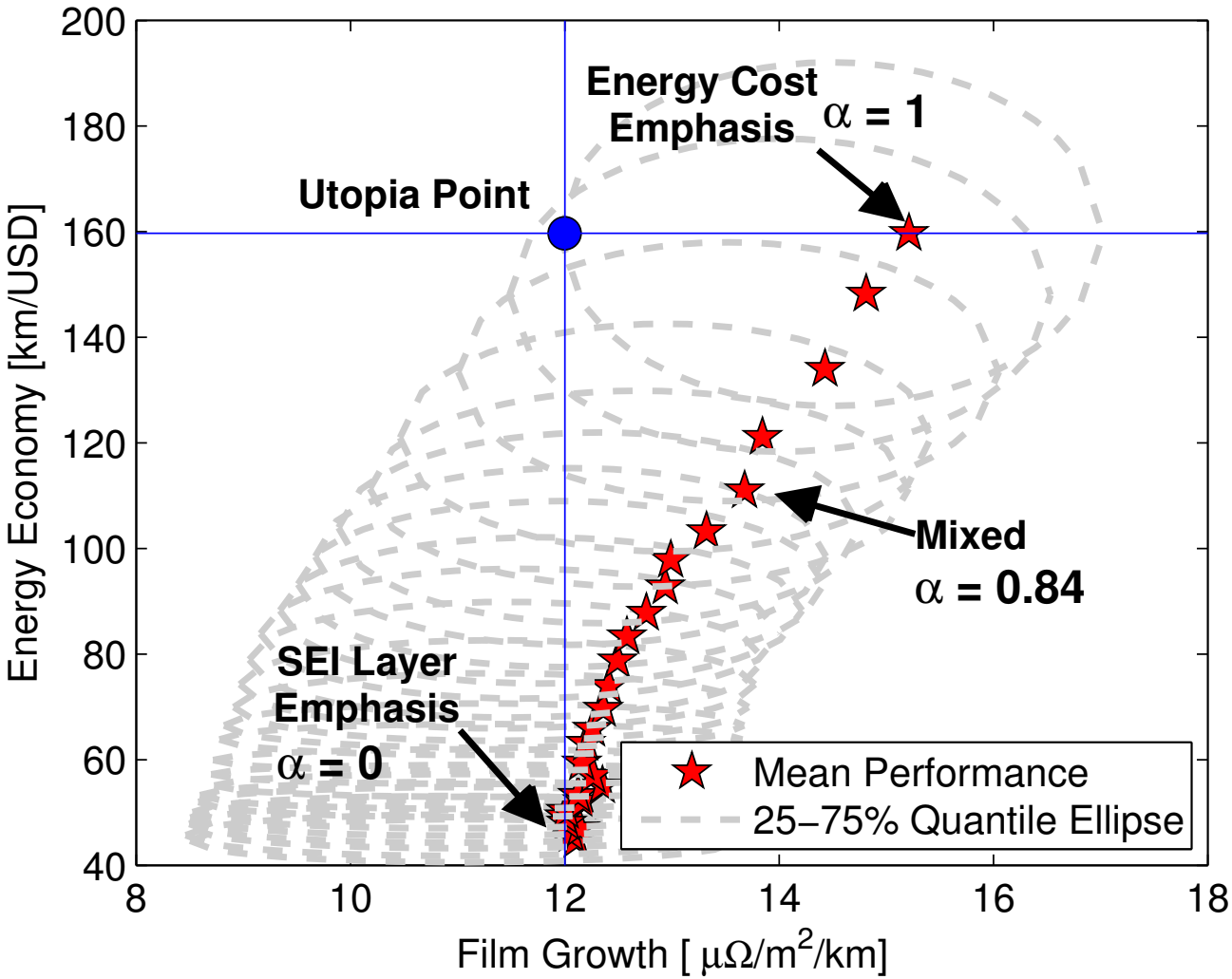
- Control Inputs
  - Engine Torque
  - M1 Torque
- State Variables
  - Engine speed
  - Vehicle speed
  - Battery SOC
  - Vehicle acceleration (Markov Chain)



Control Optimization: Minimize energy consumption cost AND battery aging

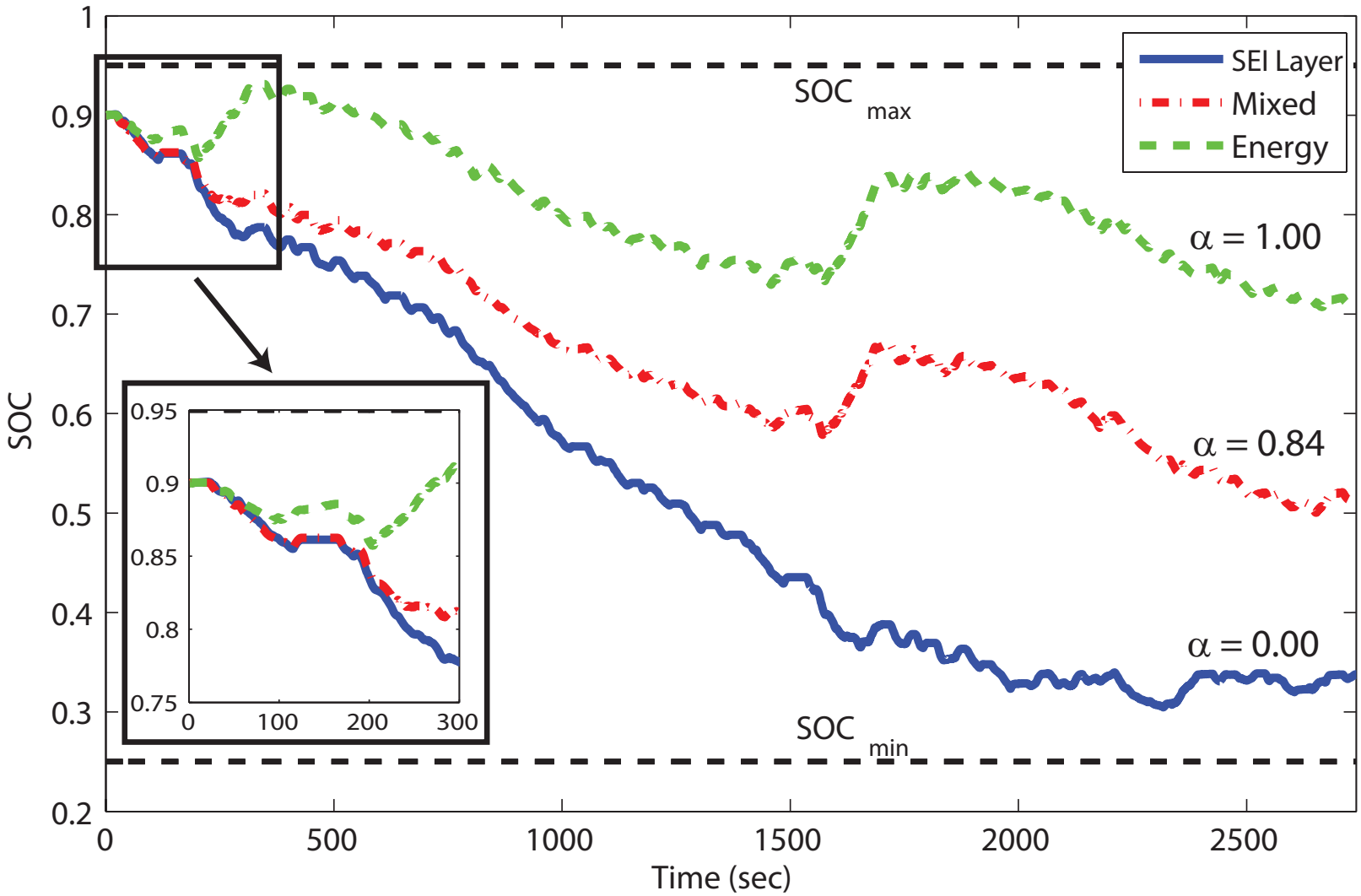
Pareto Set of Optimal Solutions

Anode-side SEI Layer Growth



SOC Trajectories

Anode-side SEI Layer Growth | UDDSx2

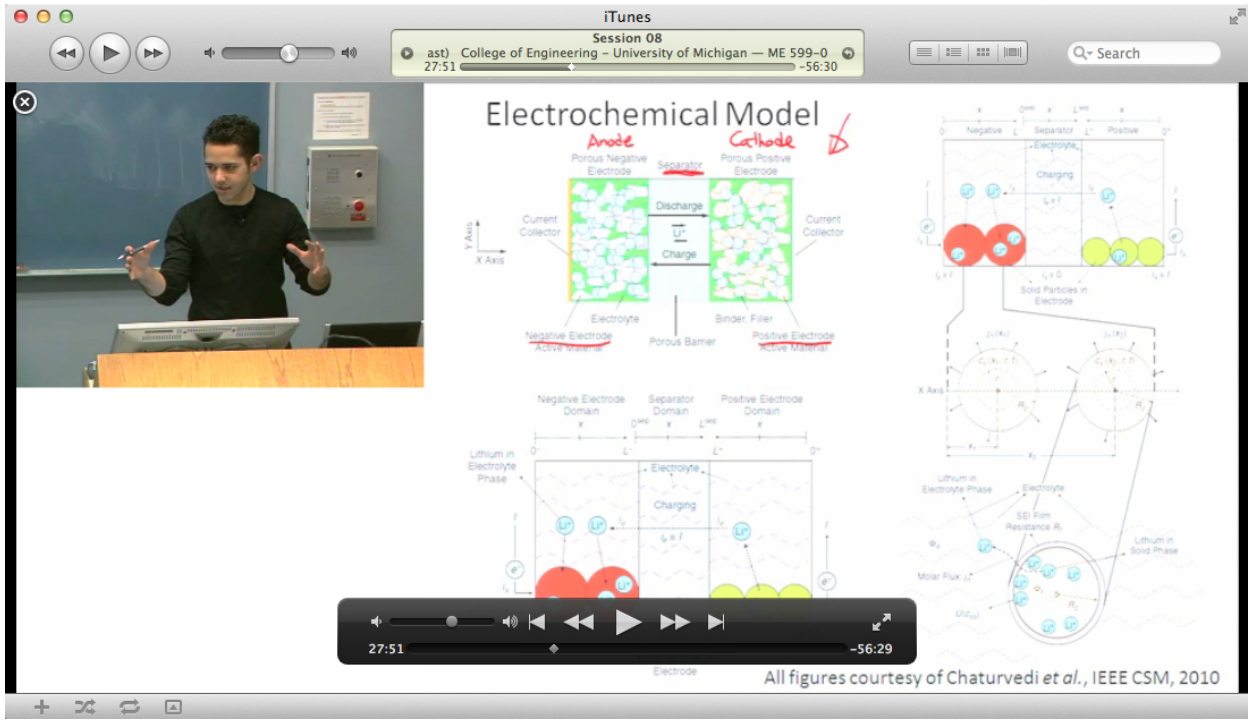


Battery Systems and Control Course

Funded by DOE-ARRA, University of Michigan

Enrollment

- Winter 2010: 59 + 5 distance
- Winter 2011: 50 + 26 distance
- ME, EE, ChemE, CS, Energy Systems, MatSci, Physics, Math
- Undergraduates
- Graduate students
- Professionals
  - Tesla Motors, General Motors, Roush, US Army



Summary of Contributions

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

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

PHEV power management
using electrochemical models
and stochastic optimal control.

Impact through education.

Energy Crisis Solutions

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

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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

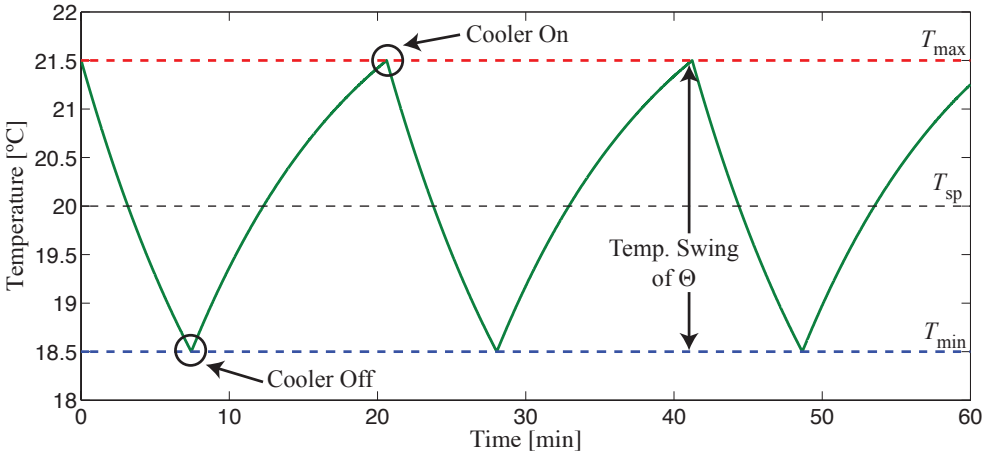
Flexible loads (e.g. TCLs) can absorb variability in renewable generation

Modeling Aggregations of TCLs

Individual TCL models

⇓

(Tens of) Thousands of hybrid ODEs

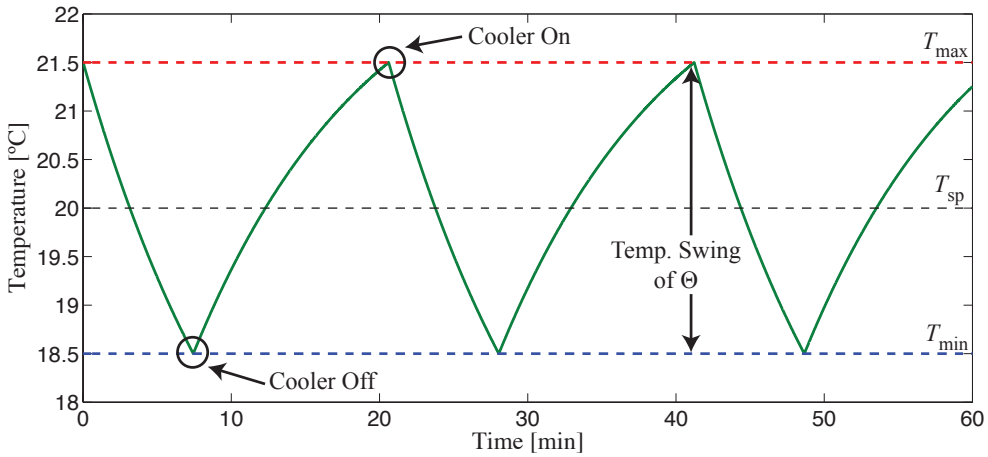


Modeling Aggregations of TCLs

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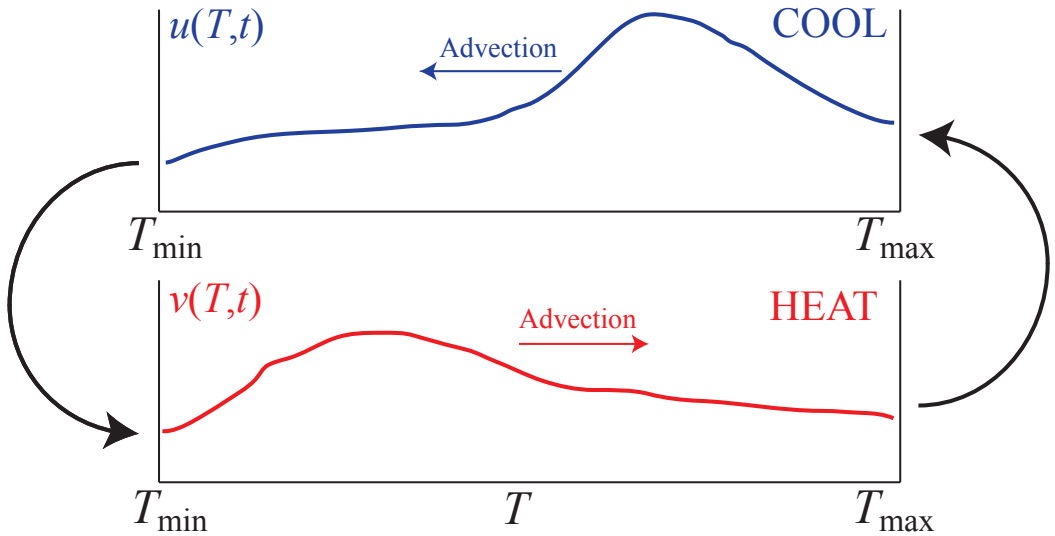
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Model **aggregations** of TCLs

⇓

Two coupled linear PDEs

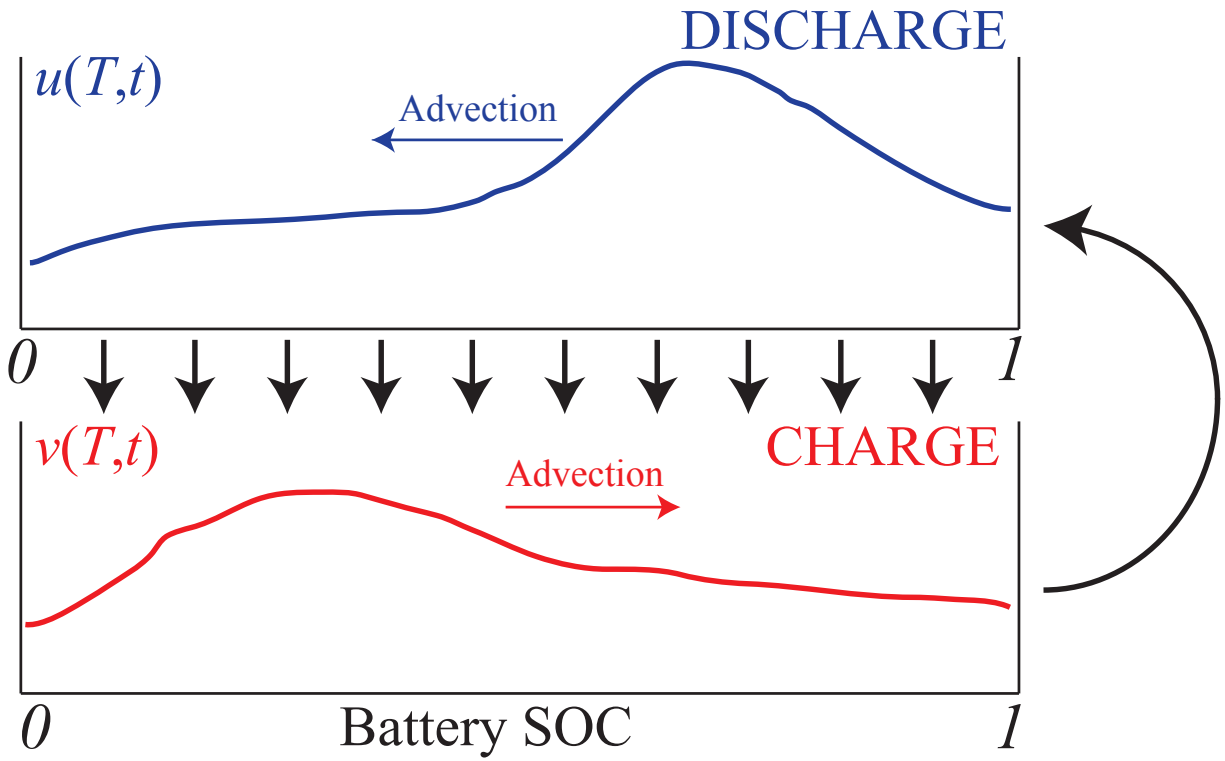


$u(T,t)$	# TCLs/°C, in COOL state, @ temp T, time t
$v(T,t)$	# TCLs/°C, in HEAT state, @ temp T, time t

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



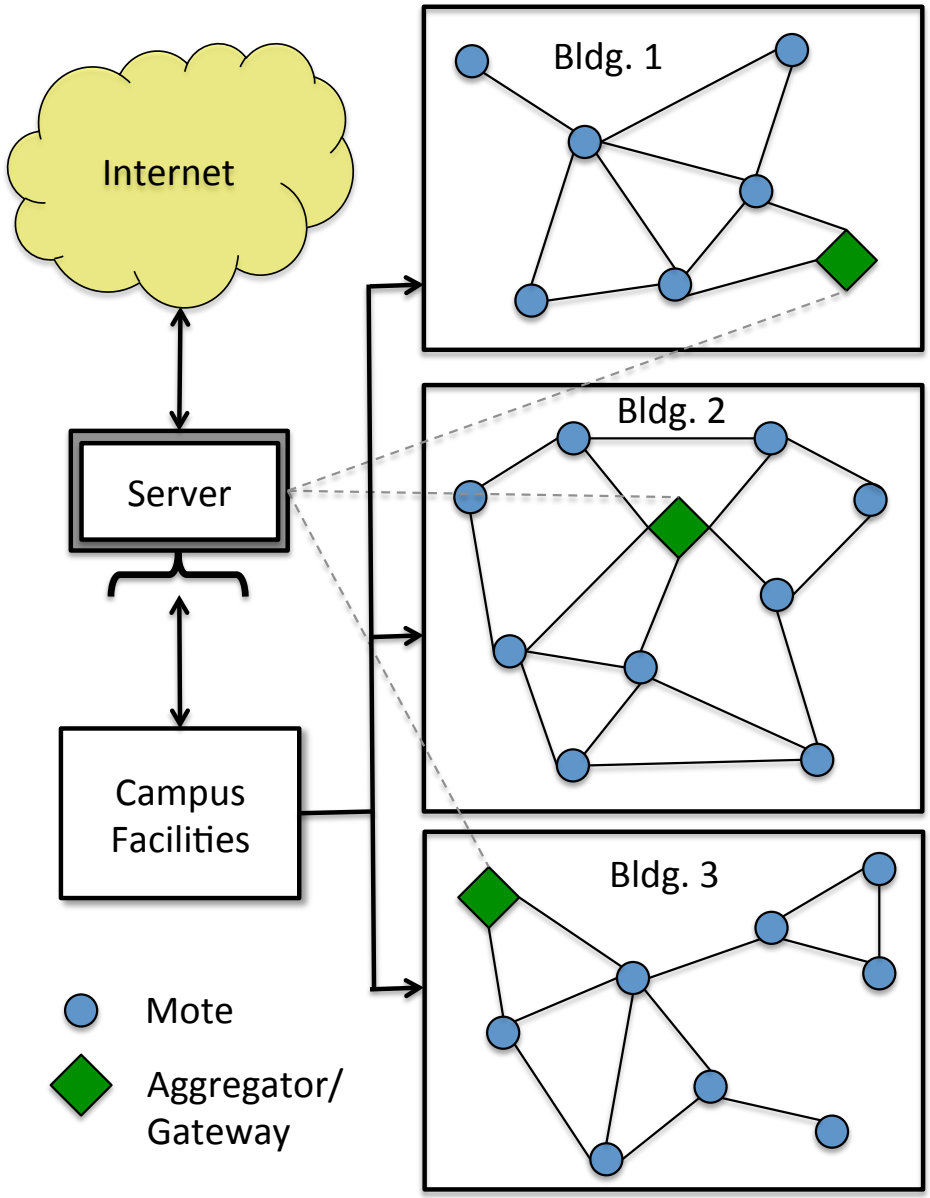
University Campus: A Living Laboratory

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

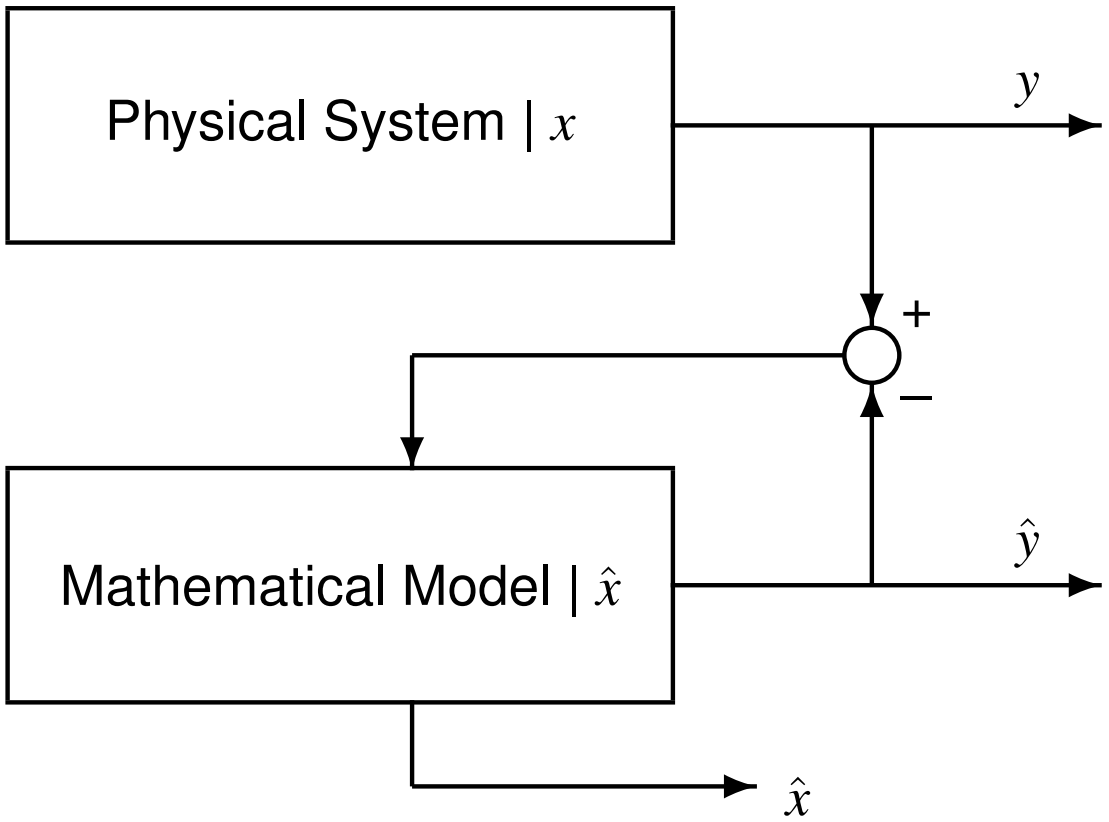
Vision: Enhanced energy, power, chg times, life from existing batts.

Open technical problems for BMS:
(1) State observability

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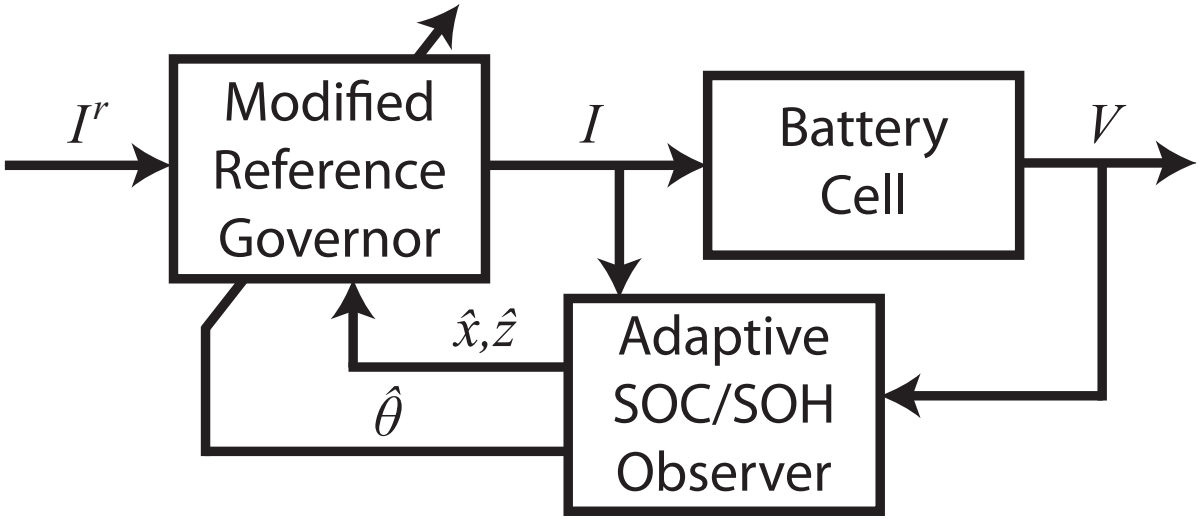
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Future: EChem-based Battery Management Systems

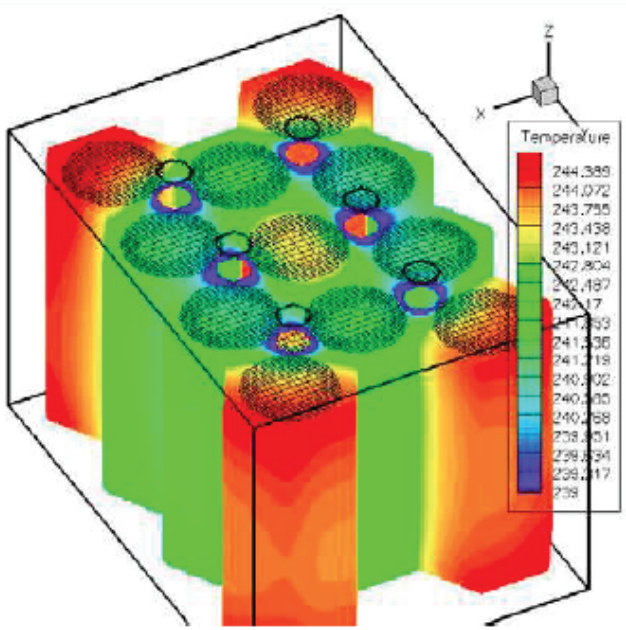
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Open technical problems for BMS:

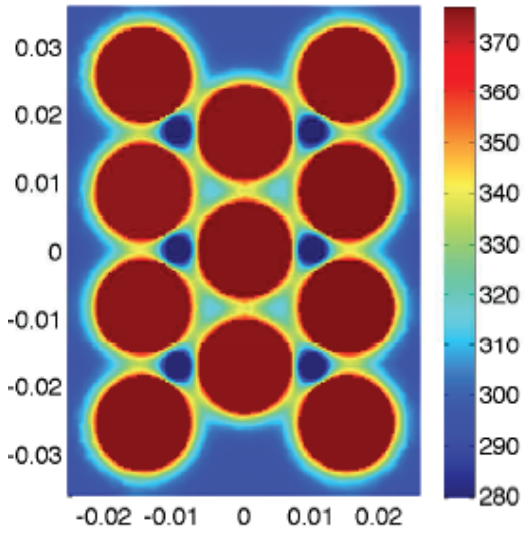
(1) State observability

(2) Output feedback

(3) Thermal management



CFD simulation

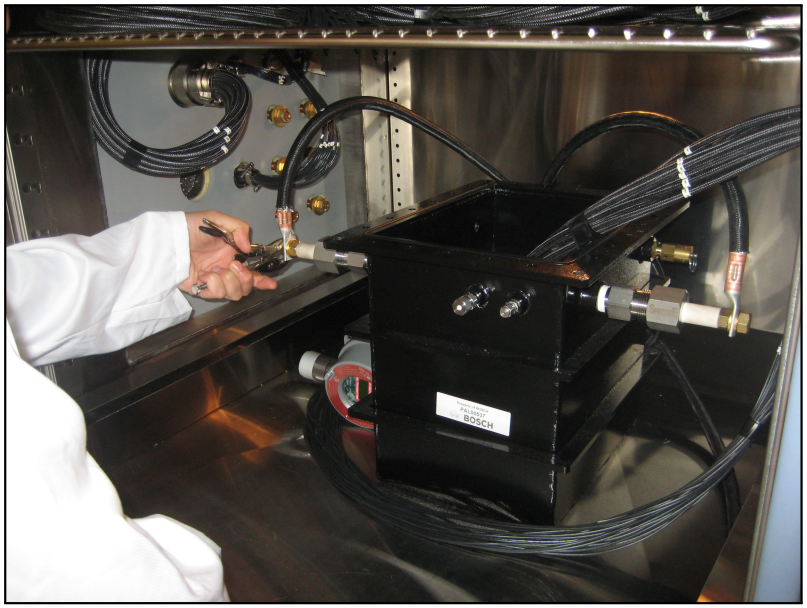


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Collaborators:

- UCSD, University of Michigan
- Bosch RTC, Ford Motor Company
- Auto Lab, UofM Energy Institute, US-China Clean Energy Research Center, Automotive Research Center, InterPro

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Funding:

- ARPA-E AMPED
- DoD HESM

Future: Solve EV Mobility - Modular Battery Packs

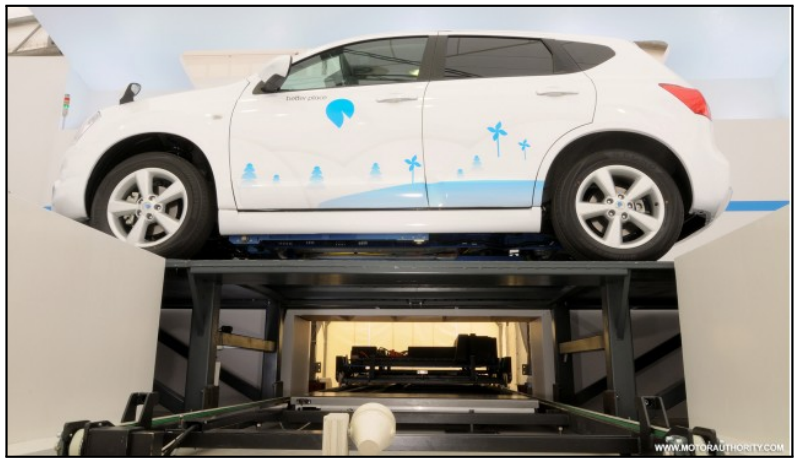
Goal: Solve range anxiety

Future: Solve EV Mobility - Modular Battery Packs

Fast Charging



Battery Swapping



Future: Solve EV Mobility - Modular Battery Packs

Modular User-Replaceable Batts

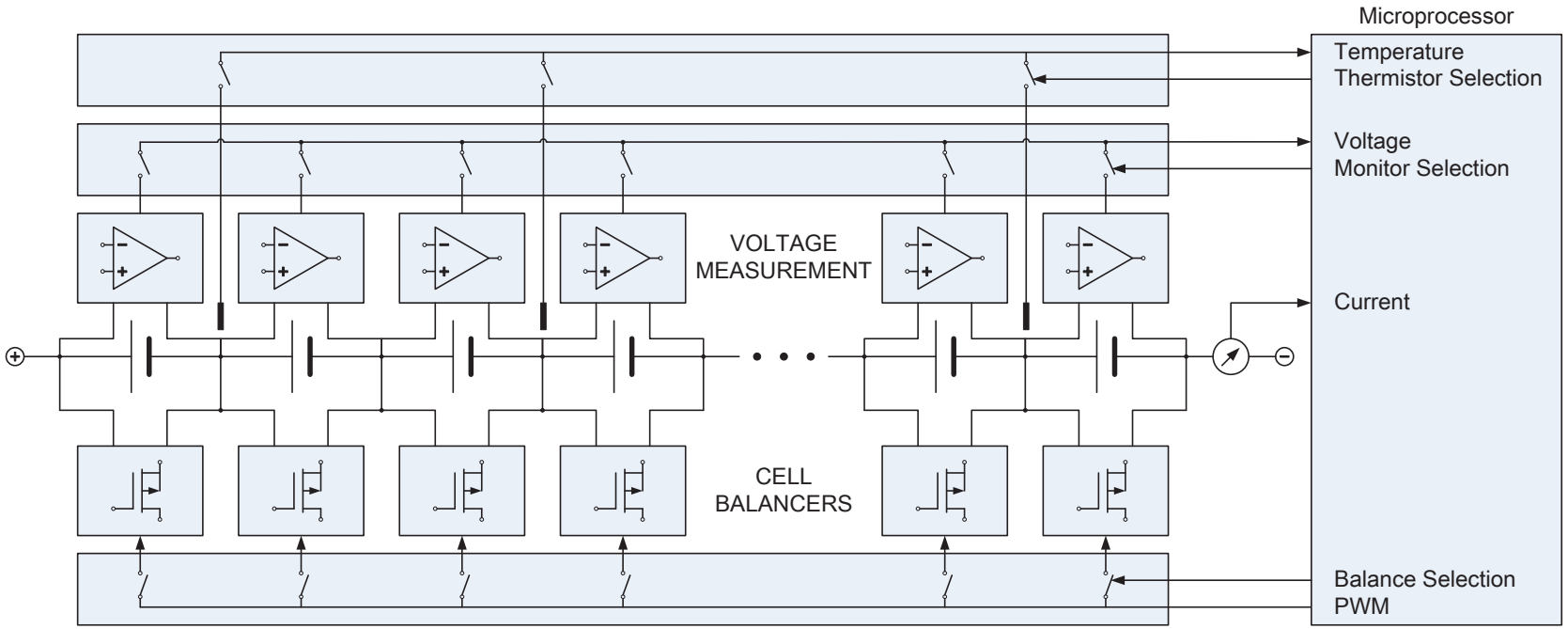


Scalable to EVs?

Future: Solve EV Mobility - Modular Battery Packs

Key components:

(1) Battery Autonomous Architecture (BAM)

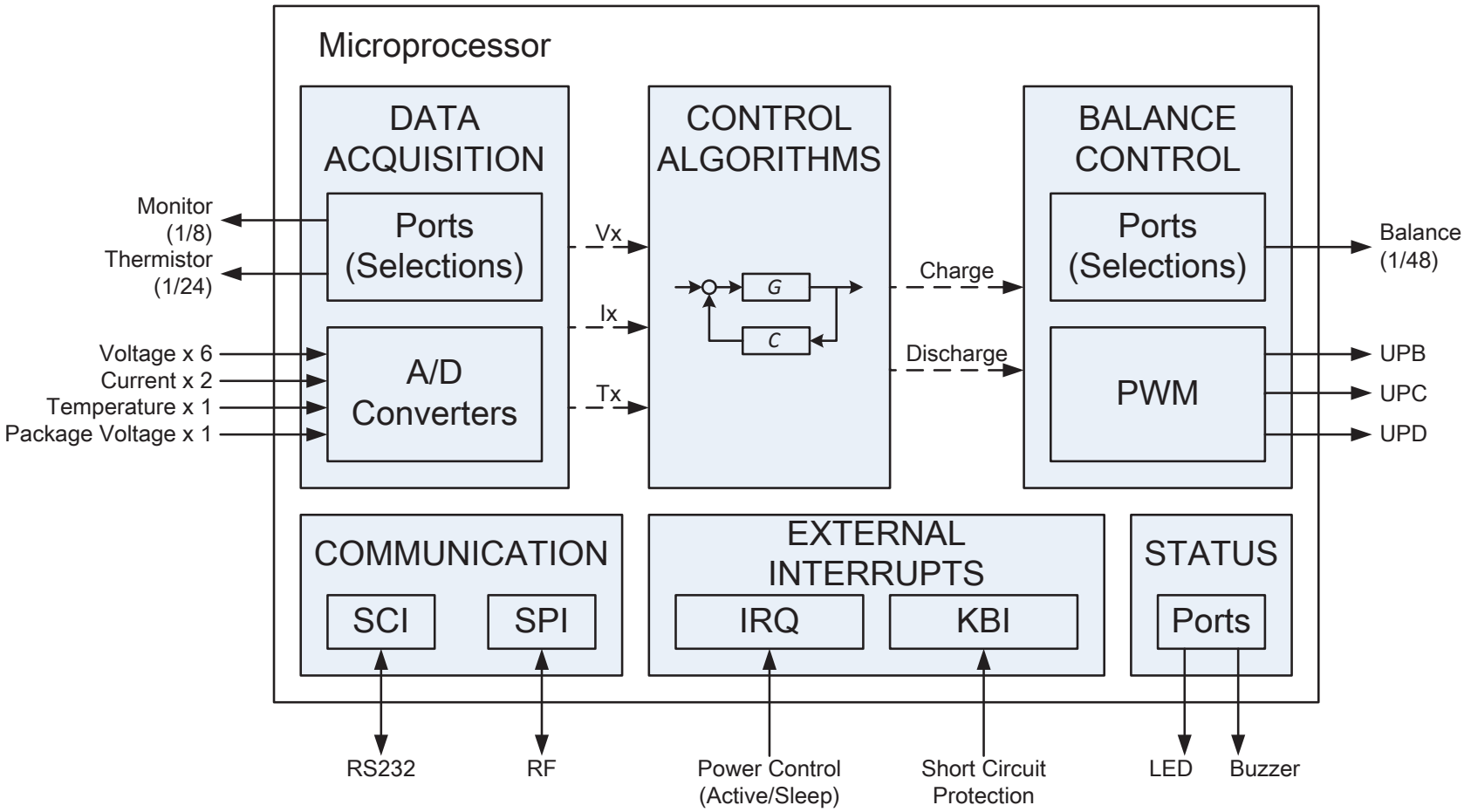


Future: Solve EV Mobility - Modular Battery Packs

Key components:

(1) Battery Autonomous Architecture (BAM)

(2) Battery Management System (BMS)



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?

Future: Solve EV Mobility - Modular Battery Packs

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Collaborators:

- UCSD, Carnegie Mellon Univ.
- Pacific Battery Management Systems
- Auto Lab (ME), Center for Sustainable Systems (SNRE), Optimal Design Lab (ME), Power & Energy Group (EECS), US-China Clean Energy Research Center

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Funding:

- ARPA-E RANGE
- Automotive Industry

Future: Demand-side Management

Vision: A fundamental systems science for demand response.
Apps: Buildings & PEVs

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Open technical problems for Coupled PDEs:

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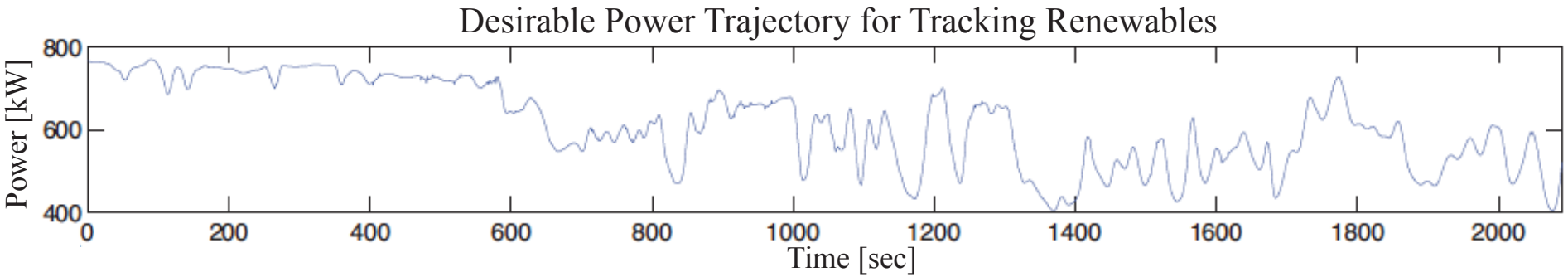
Open technical problems for Coupled PDEs:
(1) System ID & State Estimation

$$
\begin{aligned}
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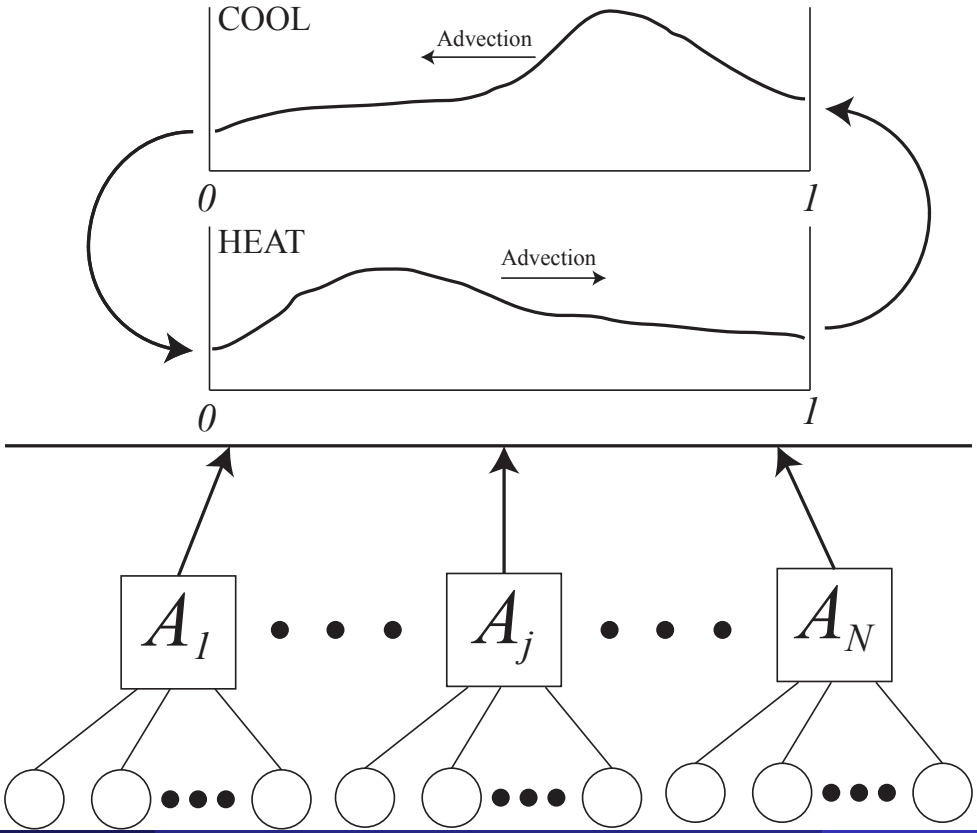
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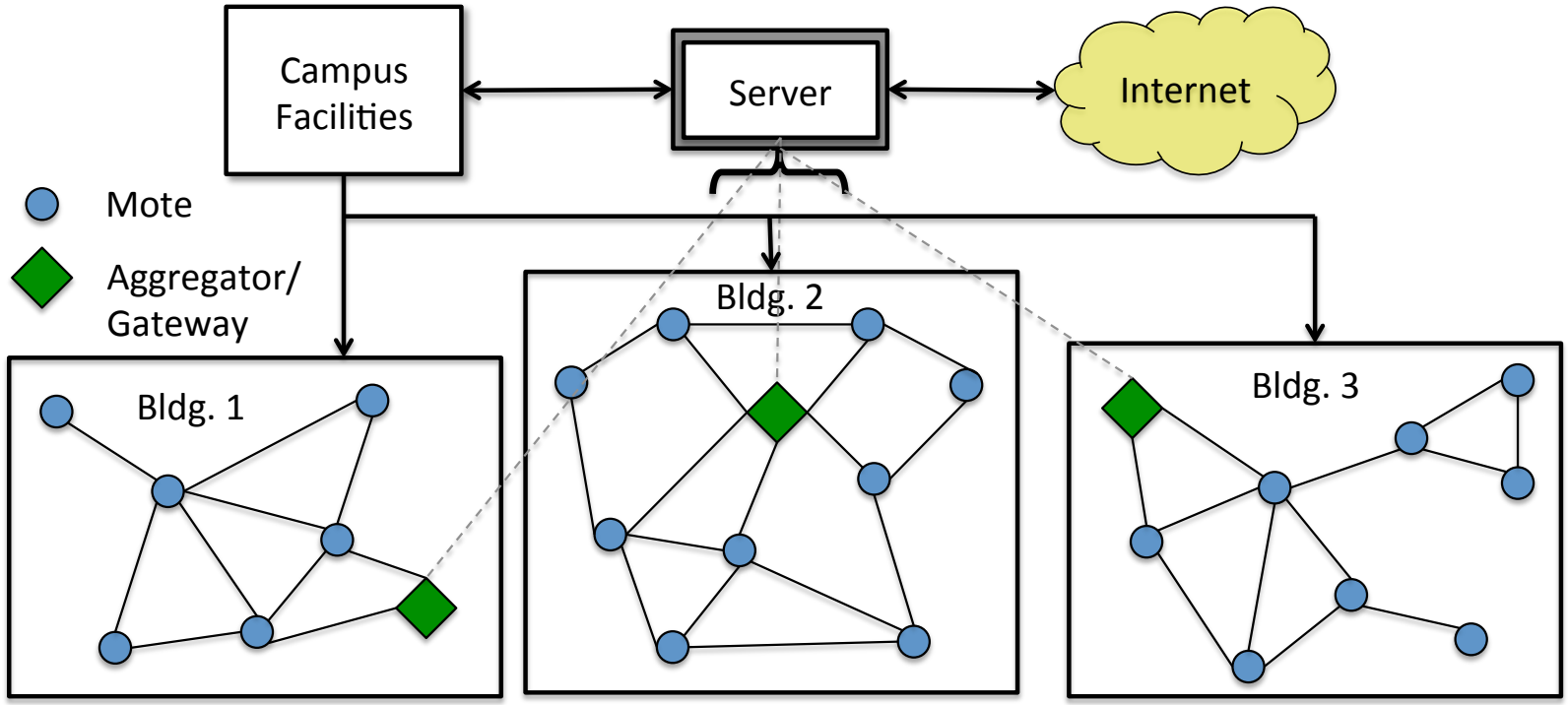
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Funding:

- DOE EERE
- NSF EPAS, CPS

Courses I could teach

Undergrad

ME 240 - Intro to Dynamic and Vibrations
ME 360 - Modeling, Analysis, and Control of Dynamic Systems
ME 433 - Advanced Energy Solutions
ME 461 - Automatic Control

Graduate

ME 502 - Methods of Differential Equations in Mechanics
ME 561 - Design of Digital Control Systems
ME 564 - Linear Systems Theory
ME 566 - Modeling, Analysis, and Control of HEVs
ME 569 - Control of Adv. Powertrain Systems
ME 662 - Advanced Nonlinear Control

Special Courses

ME 499/599 - Battery Systems and Control
NEW - Control of Distributed Parameter Systems

my lab...

Themes: systems & control | energy & transportation

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Key Tools:

- PDE modeling
- Lyapunov stability
- Adaptive control
- Optimization

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Theory/Computational	67%	33%	Experimental

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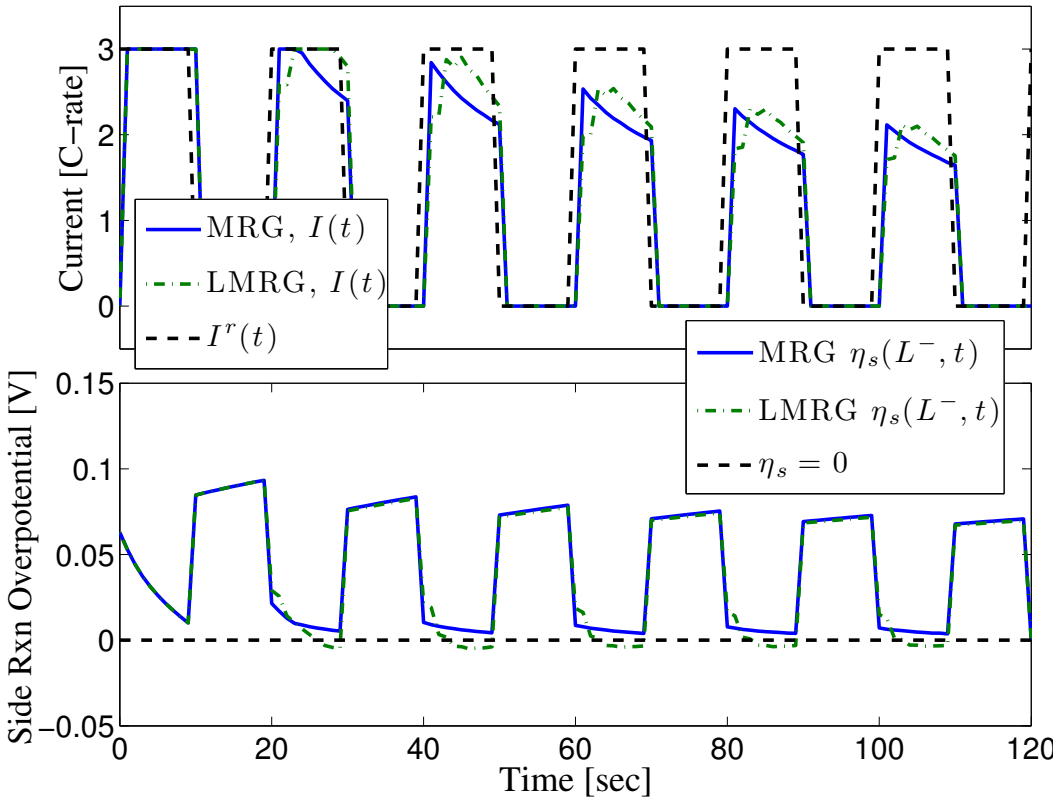
Outreach, Diversity, and Inclusion

- SHPE, NSBE, SWE
- SMES-G, Grad Admissions

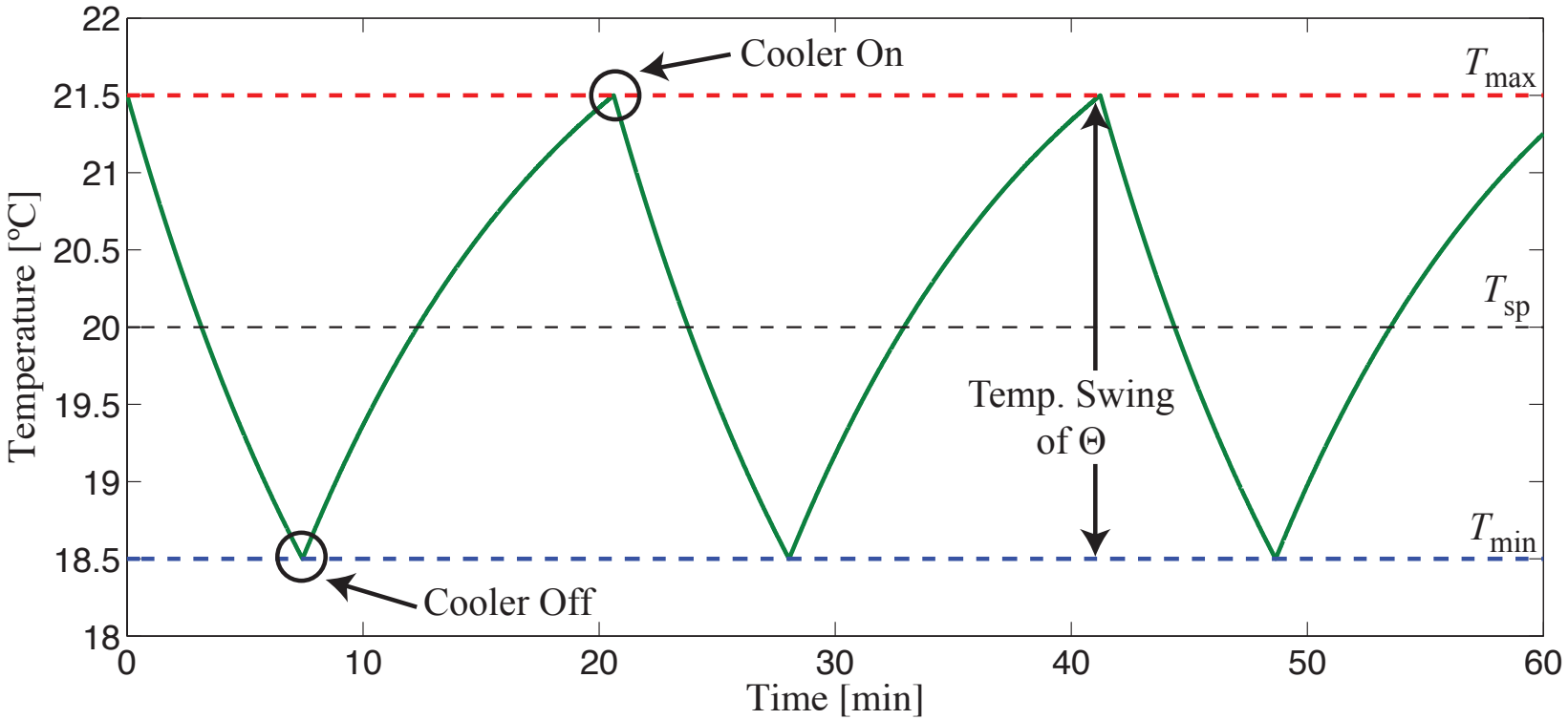

Publications available at http://flyingv.ucsd.edu/smoura/
smoura@ucsd.edu

Linear Modified Reference Governor

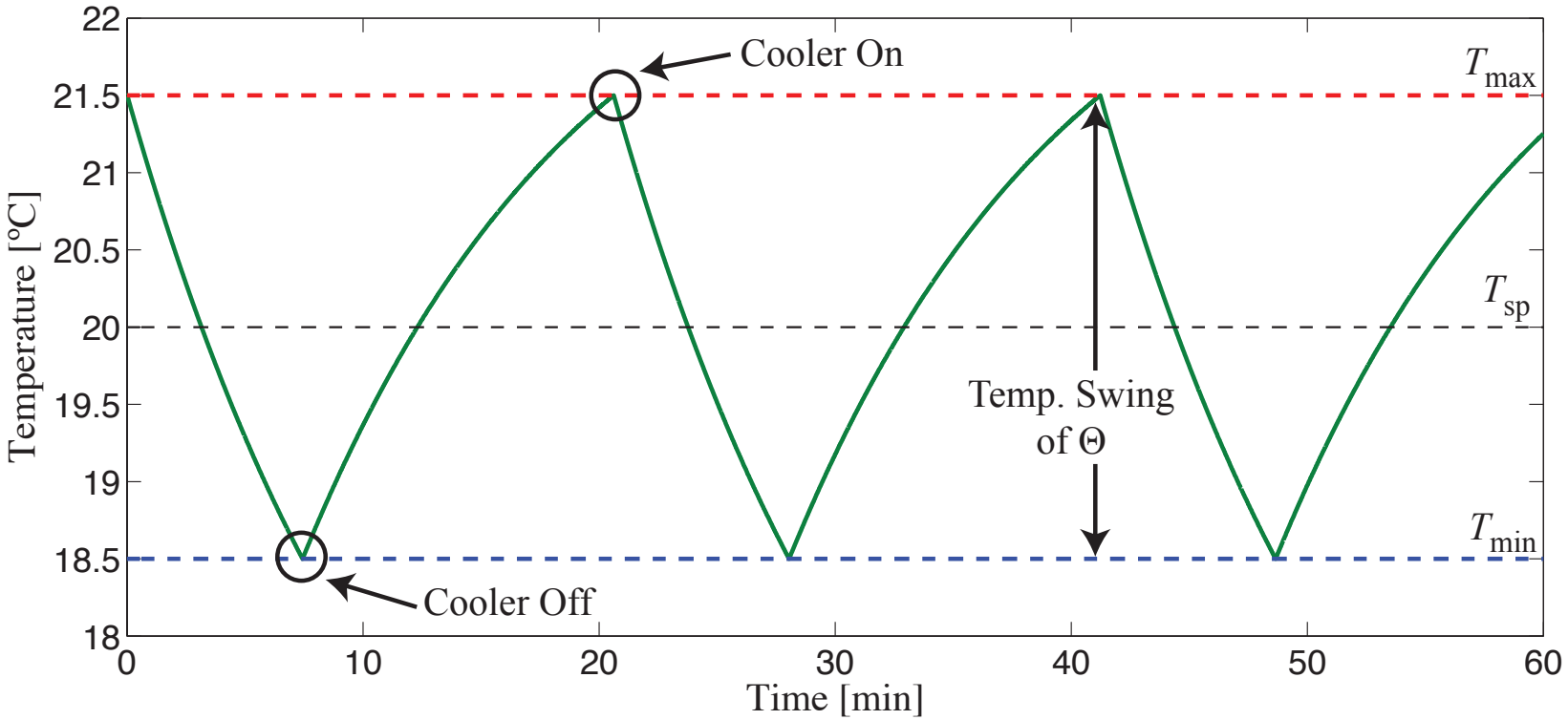
Modified Reference Governor (MRG) : Simulations
Linearized MRG (LMRG) : Explicit function evaluation



Modeling TCLs



Modeling TCLs



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

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

Modeling Aggregated TCLs

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

Modeling Aggregated TCLs

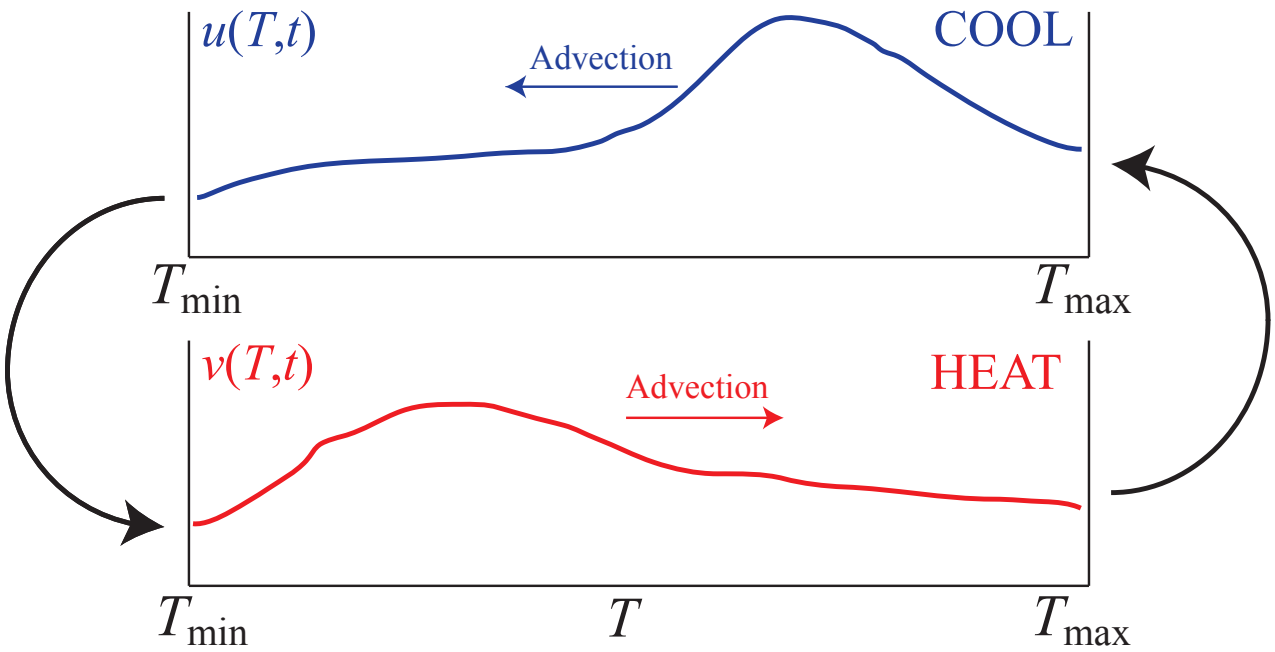
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$u(T,t)$	# TCLs / °C, in COOL state, @ temp T, time t
$v(T,t)$	# TCLs / °C, in HEAT state, @ temp T, time t

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Flux of TCLs in HEAT state:
#TCLs / sec

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

Modeling Aggregated TCLs

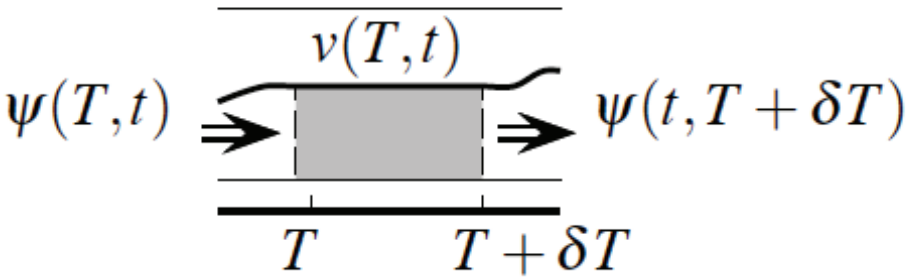
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Control volume:



Modeling Aggregated TCLs

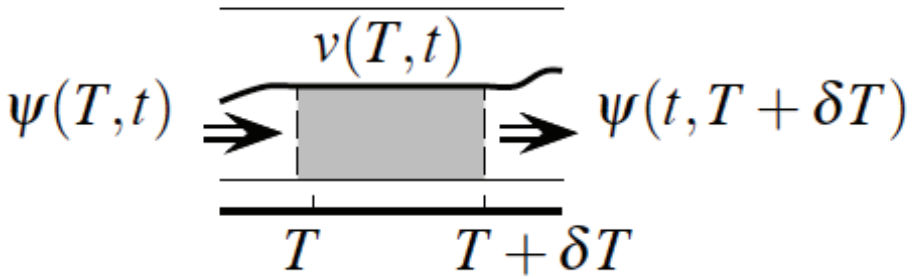
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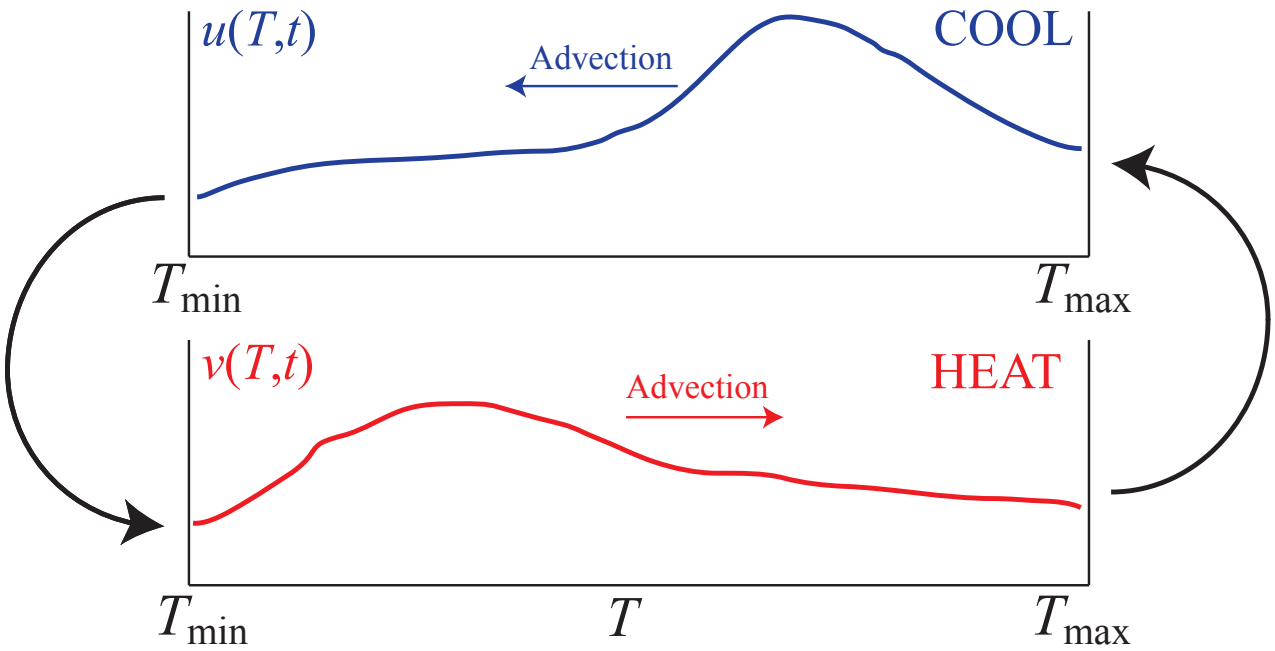
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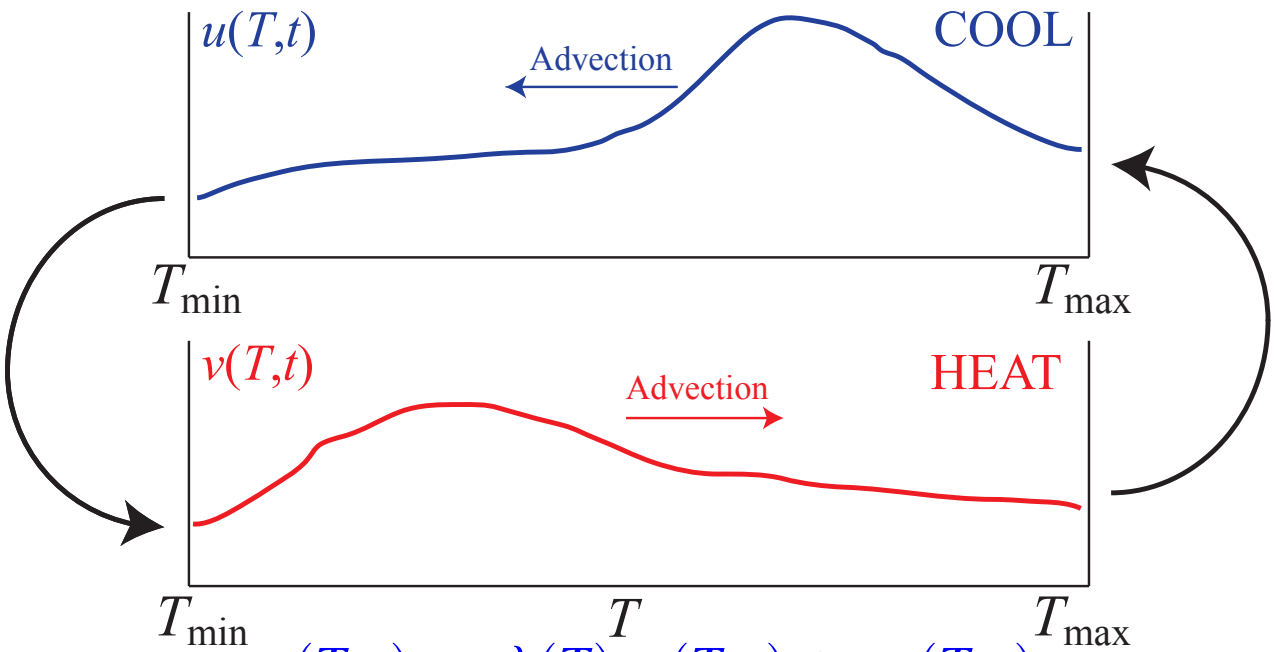


$$\begin{aligned}\frac{\partial v}{\partial t}(T,t) &= \lim_{\delta T \to 0}\left[\frac{\psi(T+\delta T,t)-\psi(T,t)}{\delta T}\right] \\ &= \frac{\partial \psi}{\partial T}(T,t) \\ &= -\frac{1}{RC}\left[T_\infty - T(t)\right]\frac{\partial v}{\partial T}(T,t) + \frac{1}{RC}v(T,t)\end{aligned}$$

PDE Model of Aggregated TCLs



PDE Model of Aggregated TCLs



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

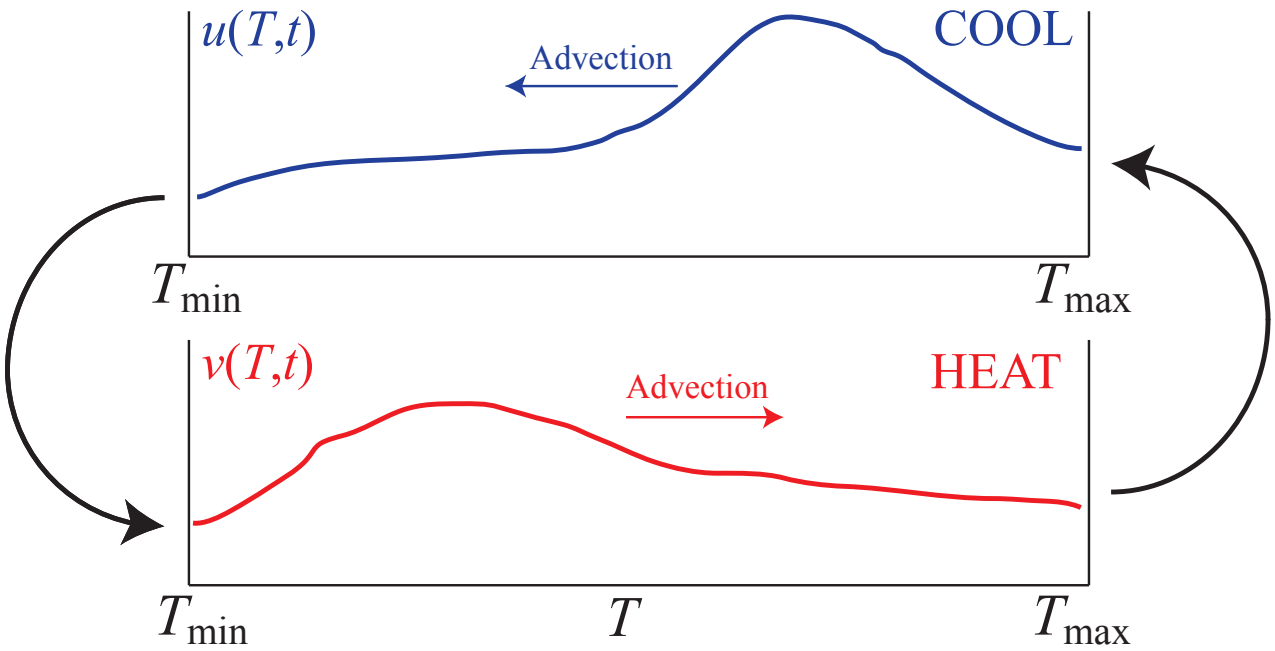
$$v_t(T,t) = -\alpha\mu(T)v_T(T,t) + \alpha v(T,t)$$

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

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

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

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

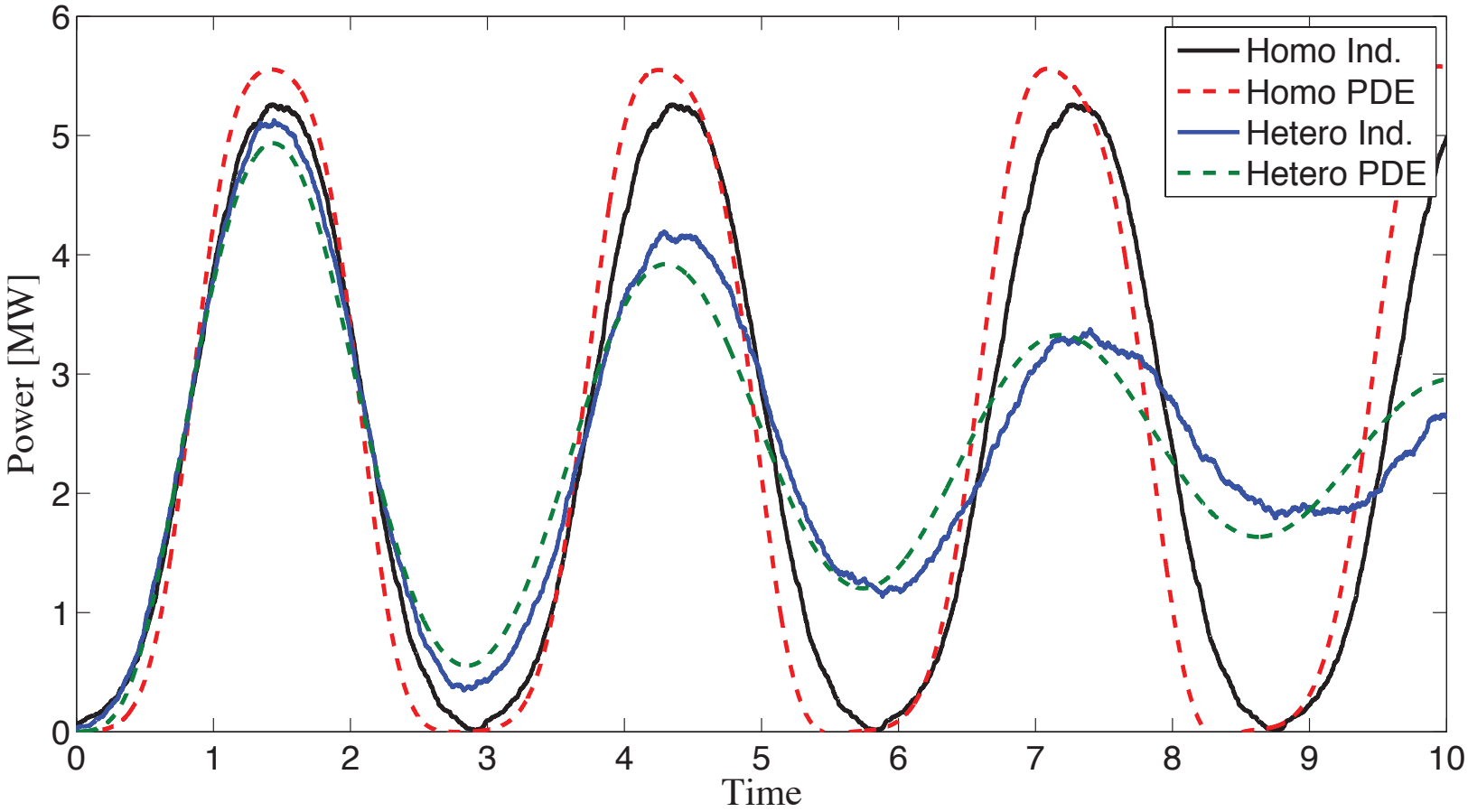
Proposition: The total number of TCLs is conserved over time.

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

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

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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Answer: YES! Using HVAC on/off signals only and state estimation

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Problem Statement

Estimate states $u(T,t), v(T,t)$ from measurements of HVAC on/off signals

The State Estimation Problem

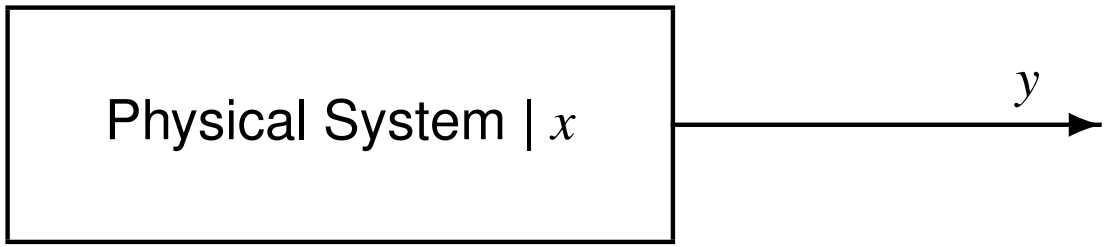
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Intro to Estimation



The State Estimation Problem

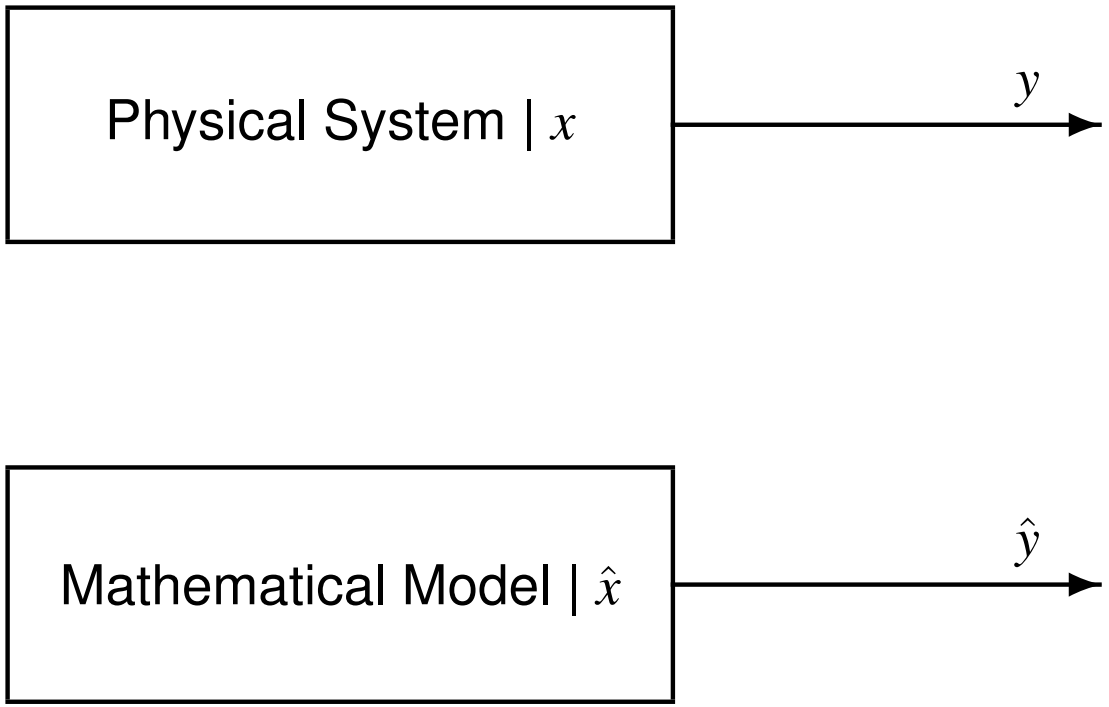
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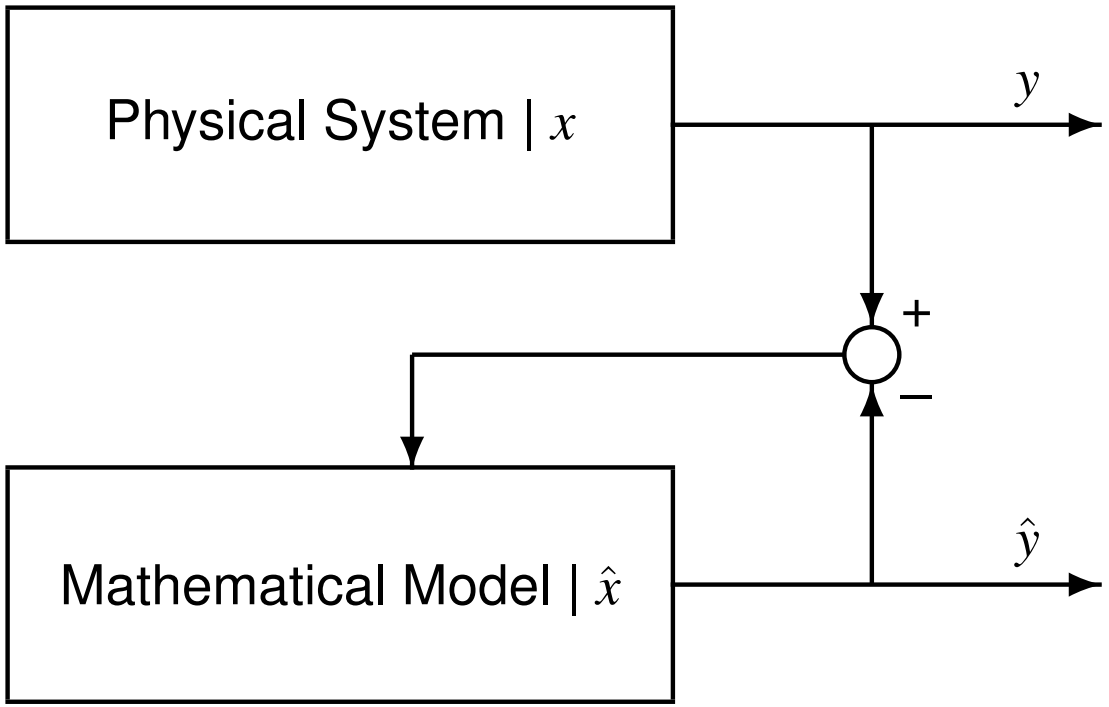
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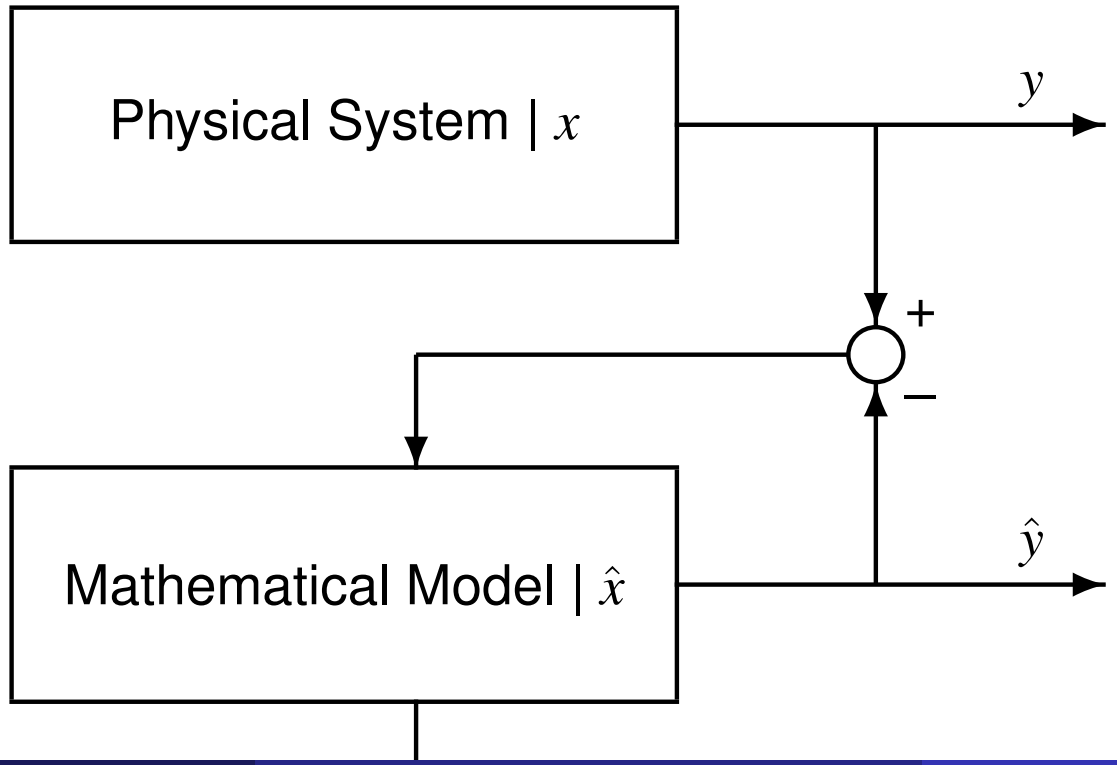
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Intro to Estimation



PDE State Estimator

Heterogeneous PDE Model: (u, v)

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

PDE State Estimator

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

$$\hat{u}_t(x,t) = \alpha\lambda(x)\hat{u}_x + \alpha\hat{u} + \beta\hat{u}_{xx}$$
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$$\hat{u}(1,t) = q_1 v(1,t), \qquad \hat{u}_x(0,t) = -\hat{v}_x(0,t) + p_{10}\left[u(0,t) - \hat{u}(0,t)\right]$$
$$\hat{v}(0,t) = q_2 u(0,t), \qquad \hat{v}_x(1,t) = -\hat{u}_x(1,t) + p_{20}\left[v(1,t) - \hat{v}(1,t)\right]$$

PDE State Estimator

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

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

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

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

The time derivative along the solution trajectories

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

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.