Modeling, Estimation, and Control in Energy Systems: Batteries & Demand Response

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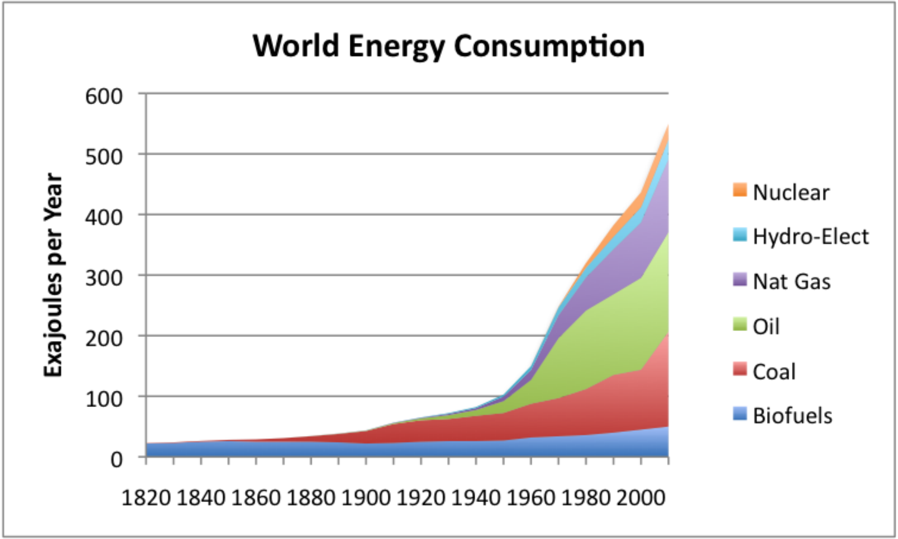

Source: Vaclav Smil Estimates from Energy Transitions

Energy Initiatives

Denmark 50% wind penetration by 2025

Brazil uses 86% renewables

China's aggressive energy/carbon intensity reduction

EV Everywhere

SunShot

Green Button

Zero emissions vehicle (ZEV)

33% renewables by 2020

Go Solar California

Energy Systems of Interest

Energy storage	Smart Grids
(e.g., batteries)	(e.g., demand response)

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Some Motivating Facts

EV Batts	1000 USD / kWh (2010)*
	485 USD / kWh (2012)*
	125 USD / kWh for parity to IC engine
	Only 50-80% of available capacity is used
	Range anxiety inhibits adoption
	Lifetime risks caused by fast charging

*Source: MIT Technology Review, "The Electric Car is Here to Stay." (2013)

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Two Solutions

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

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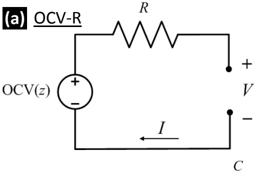
Battery Models

Equivalent Circuit Model

(a) OCV-R



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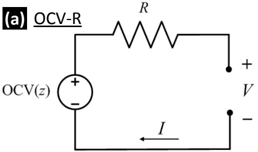
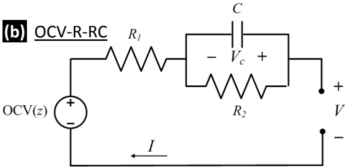
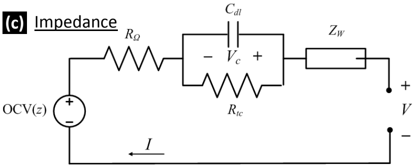


(b) OCV-R-RC



(c) Impedance



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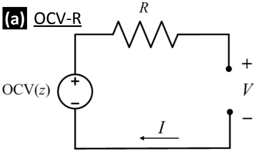

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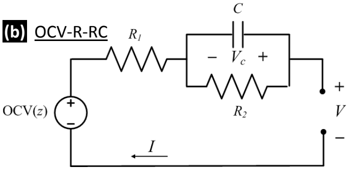

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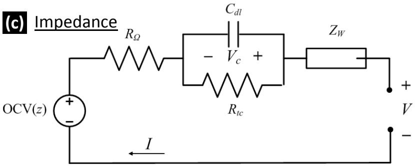
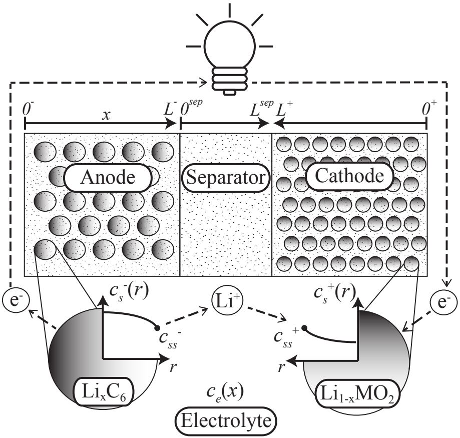
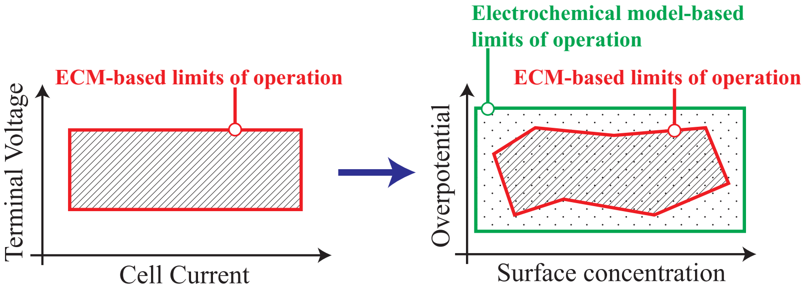


Electrochemical Model



Operate Batteries at their Physical Limits



Electrochemical Model Equations

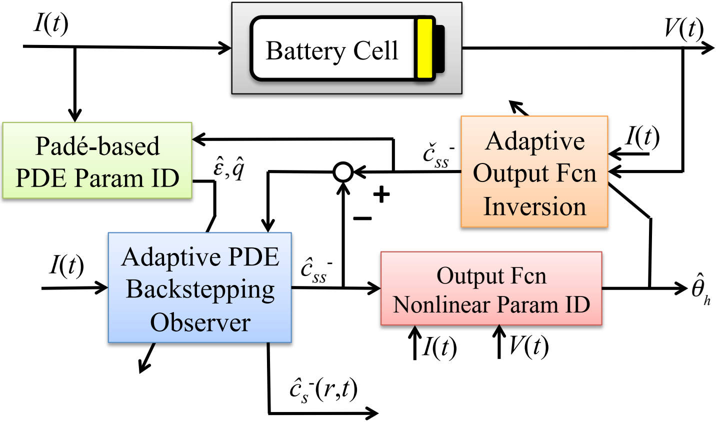
well, some of them

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

Adaptive Observer

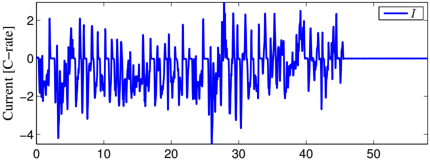
Combined State & Parameter Estimation



S. J. Moura, N. A. Chaturvedi, M. Krstic, “Adaptive PDE Observer for Battery SOC/SOH Estimation via an Electrochemical Model,” *ASME Journal of Dynamic Systems, Measurement, and Control*, 2013.

Results

UDDS Drive Cycle Input



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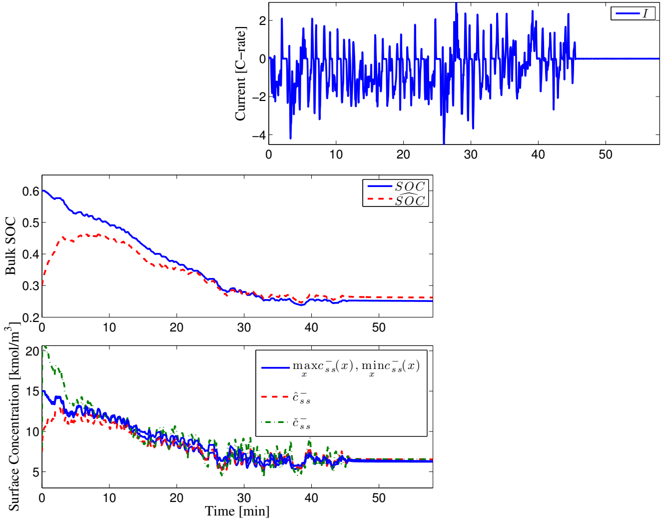

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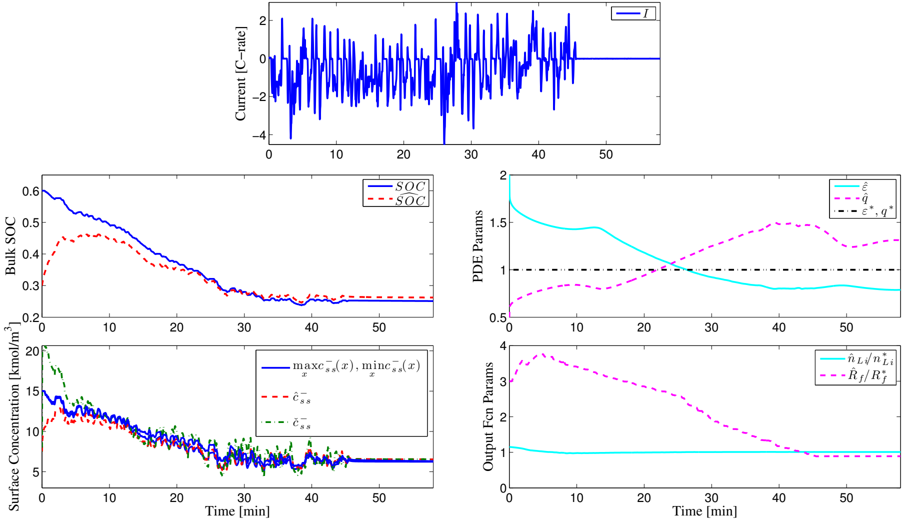
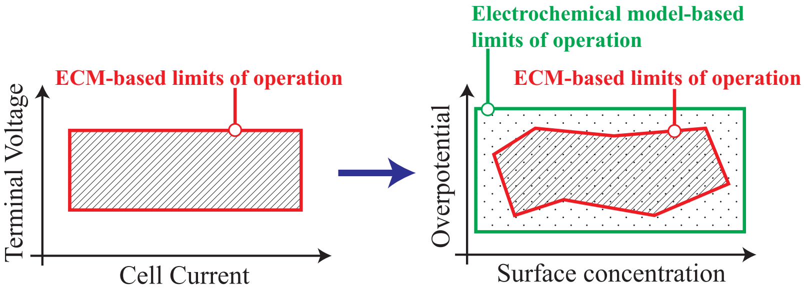


Operate Batteries at their Physical Limits

Problem Statement

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

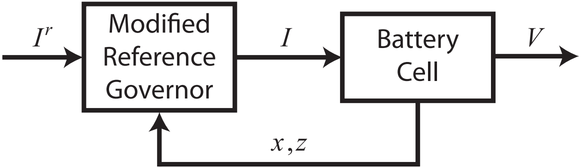


Constraints

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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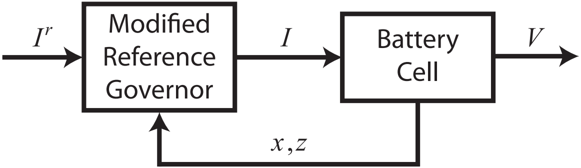

MRG Equations

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

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

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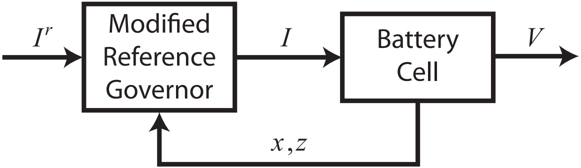

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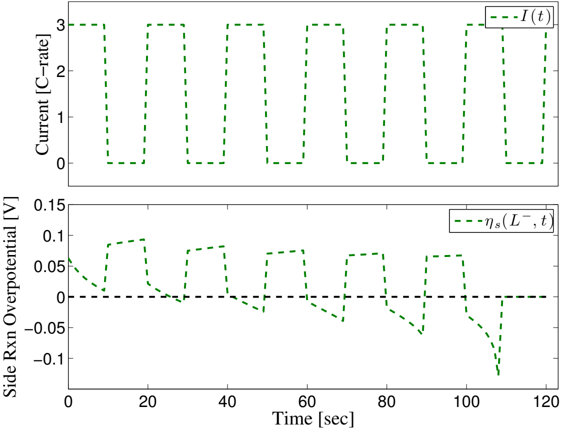
Def'n: Admissible Set $\mathcal{O}$

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

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

Constrained Control of EChem States



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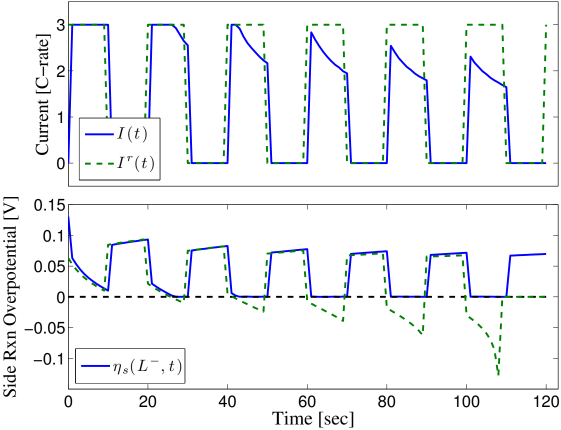
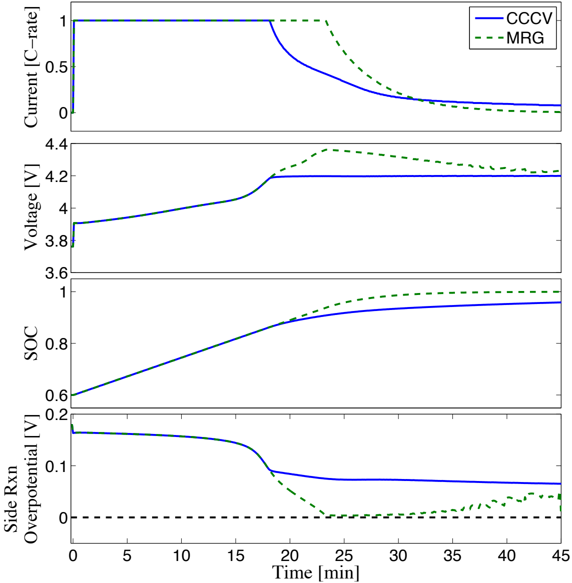


Application to Charging



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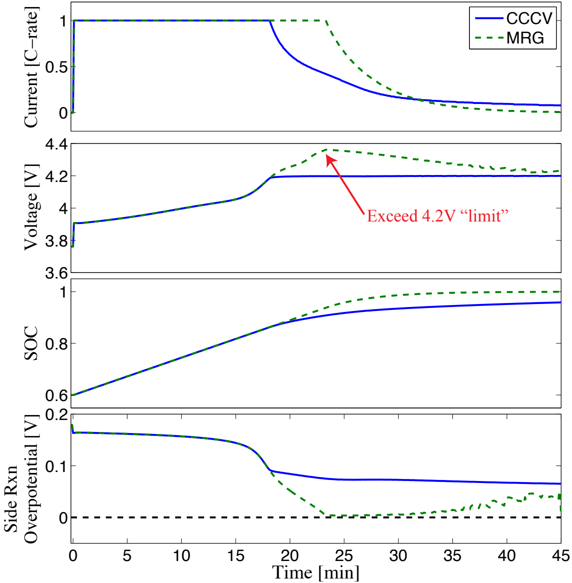

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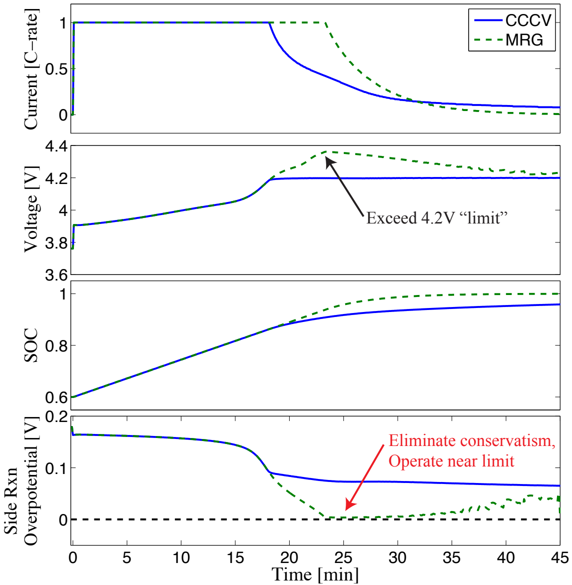

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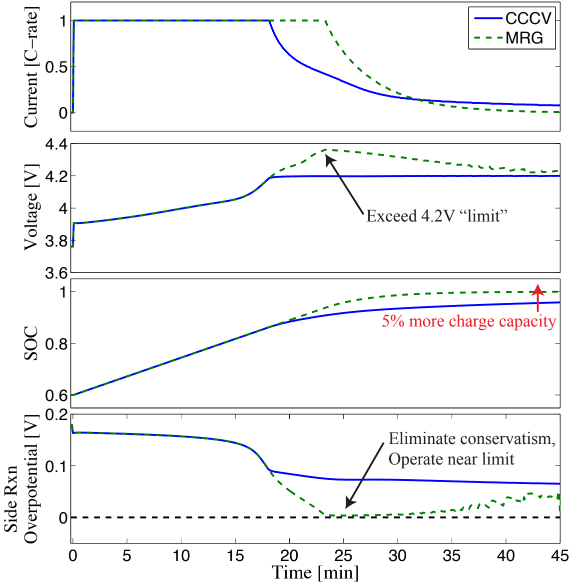

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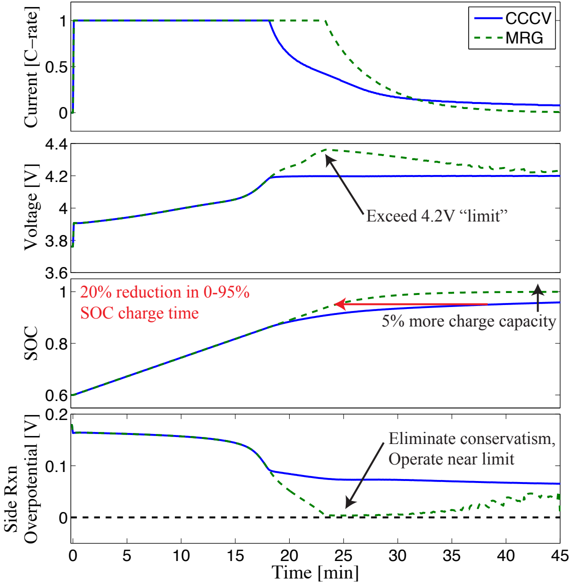
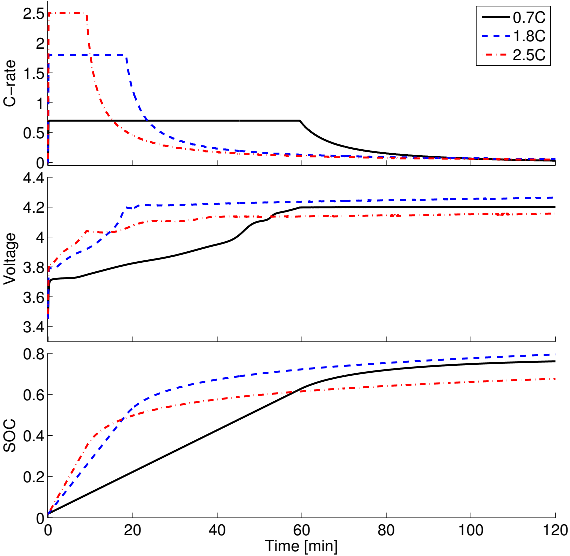


Fast Charging



Fast charge your smartphone/EV while getting coffee

Table: Simulated fast charge times for various C-rates

Charge range	**0.7C** | Traditional	**1.8C** | ECC	**2.5C** | ECC
0-10%	7.92 min	3.17 min	2.33 min
0-20%	17.83 min	7.00 min	5.08 min
0-50%	47.33 min	18.42 min	20.50 min

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2. Demand Response of TCLs
3. Coming Soon...

Energy Systems of Interest

Energy storage	Smart Grids
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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

Exploit flexibility of TCLs for power system services

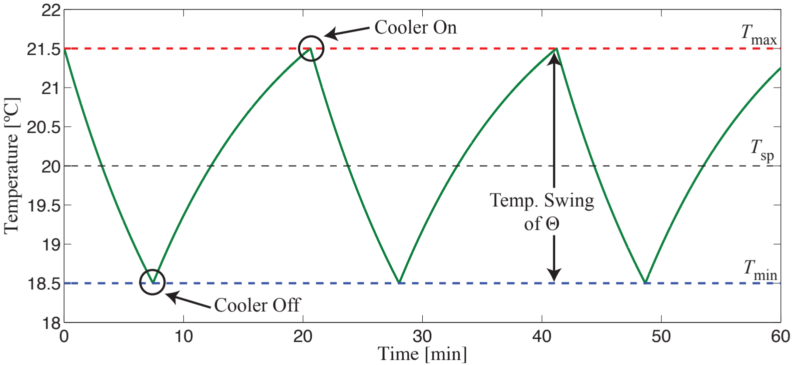
Relevant Literature (non-exclusive)

Reference	**Models***	**Control**	**ParamID**	**State Est.**
Malhame & Chong, *TAC* (1985)	FP			
Callaway, *EC&M* (2009)	FP		X	
Kundu et al., *PSCC* (2011)	IO	X		
Perfumo et al., *EC&M* (2012)	IO	X		
Bashash & Fathy, *TCST* (2013)	PDE	X		
Mathieu et al., *TPS* (2013)	MC	X	X	X
Zhang et al., *TPS* (2013)	SS	X		
SM, VR, JB, AG	PDE	X	X	X

* Fokker-Planck (FP), Input-output (IO), Partial diff. eqn. (PDE), Markov chain (MC), State-space (SS)

Models heterogeneous populations of TCLs.

Modeling TCLs



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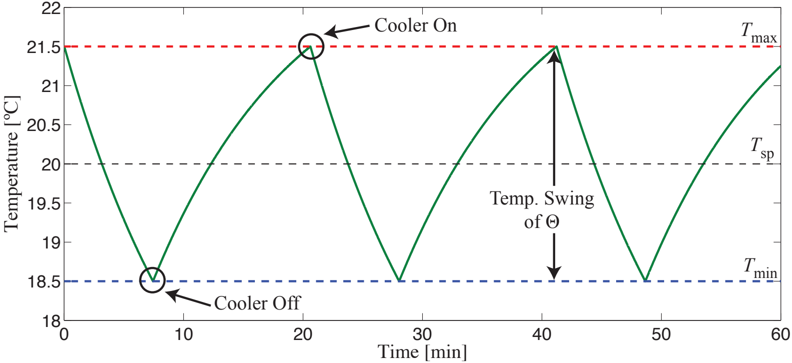

$$\dot{T}_i(t) = \frac{1}{R_i C_i}\left[T_\infty - T_i(t) - s_i(t) R_i P_i\right], \quad i = 1, 2, \ldots, N$$
$$s_i \in \{0, 1\}$$

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

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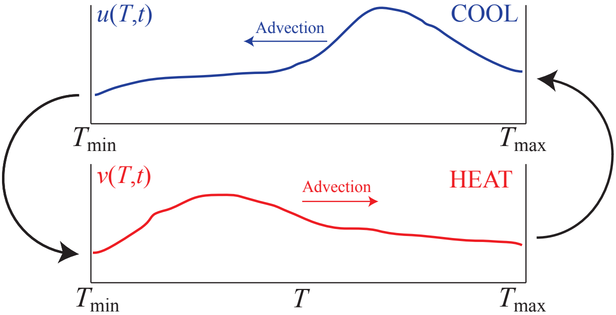

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Flux of TCLs in HEAT state:
#TCLs / sec

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

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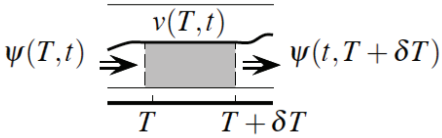
Control volume:



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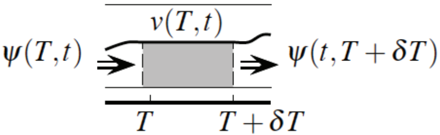
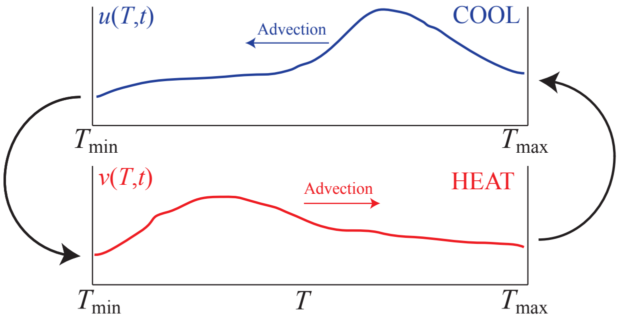


$$\begin{aligned}
\frac{\partial v}{\partial t}(T,t) &= \lim_{\delta T \to 0}\left[\frac{\psi(T+\delta T,t) - \psi(T,t)}{\delta T}\right] \\
&= \frac{\partial \psi}{\partial T}(T,t) \\
&= -\frac{1}{RC}\left[T_\infty - T(t)\right]\frac{\partial v}{\partial T}(T,t) + \frac{1}{RC} v(T,t)
\end{aligned}$$

PDE Model of Aggregated TCLs



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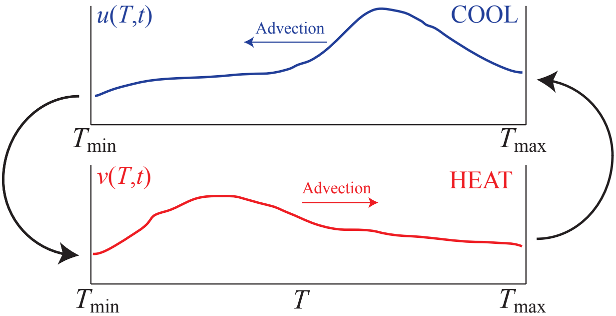

$$u_t(T,t) = \alpha\lambda(T)u_T(T,t) + \alpha u(T,t)$$

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

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

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Video of 1,000 TCLs

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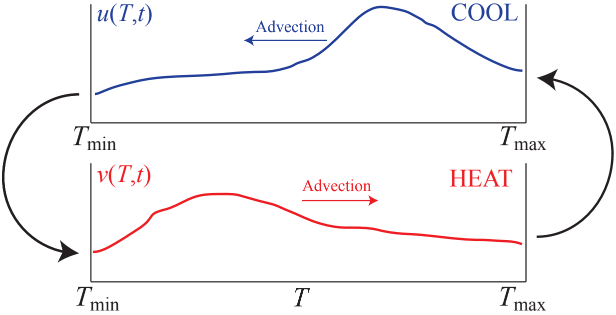

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Original Idea: Malhame and Chong, Trans. on Automatic Control (1985)

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

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\end{aligned}
$$

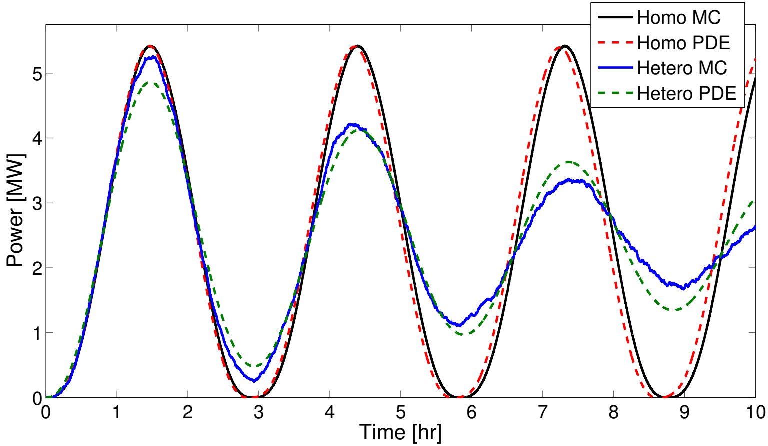
Proposition: The total number of TCLs is conserved over time.

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

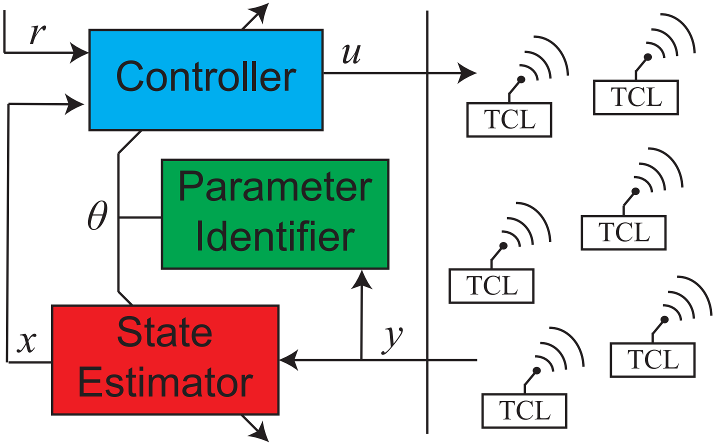
$$
\frac{dQ}{dt}(t) = 0, \qquad \forall t
$$

Video Evolution of Heterogeneous PDE

Model Comparison



Feedback Control System



PDE State Estimator

Heterogeneous PDE Model: (u, v)

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

Measurements?

- $u(0,t), v(1,t)$
- $u_x(1,t), v_x(0,t)$

PDE State Estimator

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

$$
\begin{aligned}
\hat{u}_t(x,t) &= \alpha\lambda(x)\hat{u}_x + \alpha\hat{u} + \beta\hat{u}_{xx} + p_1(x)\left[u(0,t) - \hat{u}(0,t)\right] \\
\hat{u}_x(0,t) &= -v_x(0,t) + p_{10}\left[u(0,t) - \hat{u}(0,t)\right] \\
\hat{u}(1,t) &= q_1 v(1,t) \\
\\
\hat{v}_t(x,t) &= -\alpha\mu(x)\hat{v}_x + \alpha\hat{v} + \beta\hat{v}_{xx} + p_2(x)\left[v(1,t) - \hat{v}(1,t)\right] \\
\hat{v}(0,t) &= q_2 u(0,t) \\
\hat{v}_x(1,t) &= -u_x(1,t) + p_{20}\left[v(1,t) - \hat{v}(1,t)\right]
\end{aligned}
$$

PDE State Estimator

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

$$
\begin{aligned}
\tilde{u}_t(x,t) &= \alpha\lambda(x)\tilde{u}_x + \alpha\tilde{u} + \beta\tilde{u}_{xx} - p_1(x)\tilde{u}(0,t) \\
\tilde{u}_x(0,t) &= -p_{10}\tilde{u}(0,t) \\
\tilde{u}(1,t) &= 0
\end{aligned}
$$

$$
\begin{aligned}
\tilde{v}_t(x,t) &= -\alpha\mu(x)\tilde{v}_x + \alpha\tilde{v} + \beta\tilde{v}_{xx} - p_2(x)\tilde{v}(1,t) \\
\tilde{v}(0,t) &= 0 \\
\tilde{v}_x(1,t) &= -p_{20}\tilde{v}(1,t)
\end{aligned}
$$

PDE State Estimator

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

$$\begin{aligned}
\tilde{u}_t(x,t) &= \alpha\lambda(x)\tilde{u}_x + \alpha\tilde{u} + \beta\tilde{u}_{xx} - p_1(x)\tilde{u}(0,t) \\
\tilde{u}_x(0,t) &= -p_{10}\tilde{u}(0,t) \\
\tilde{u}(1,t) &= 0
\end{aligned}$$

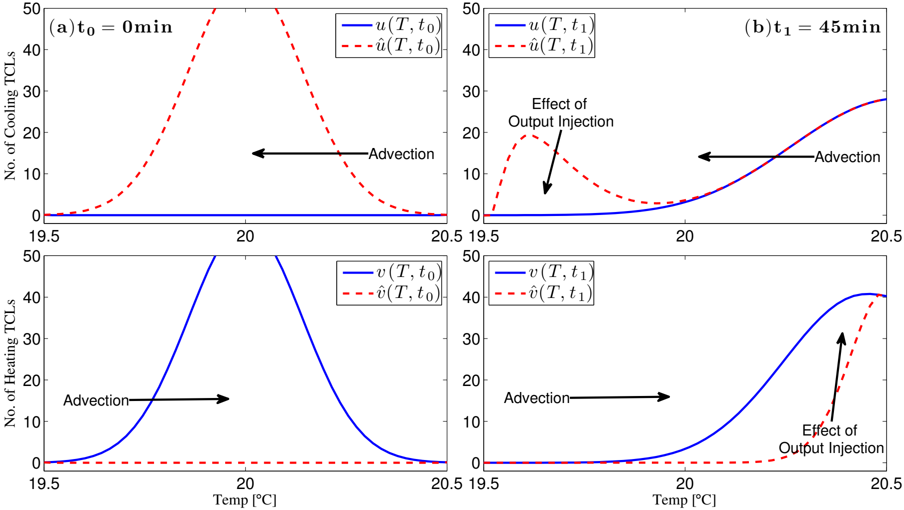
$$\begin{aligned}
\tilde{v}_t(x,t) &= -\alpha\mu(x)\tilde{v}_x + \alpha\tilde{v} + \beta\tilde{v}_{xx} - p_2(x)\tilde{v}(1,t) \\
\tilde{v}(0,t) &= 0 \\
\tilde{v}_x(1,t) &= -p_{20}\tilde{v}(1,t)
\end{aligned}$$

Goal: Design estimation gains:

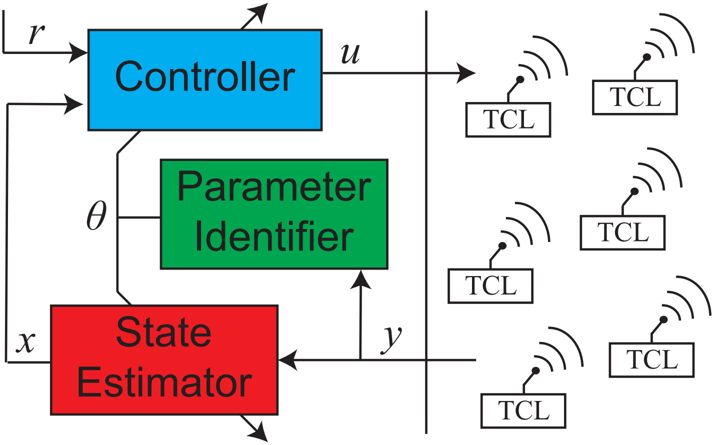
- $p_1(x), p_2(x) : (0,1) \rightarrow \mathbb{R}$
- $p_{10}, p_{20} \in \mathbb{R}$

such that $(\tilde{u}, \tilde{v}) = (0,0)$ is exponentially stable

Simulations



Feedback Control System



Parameter Identification

Uncertain parameters

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

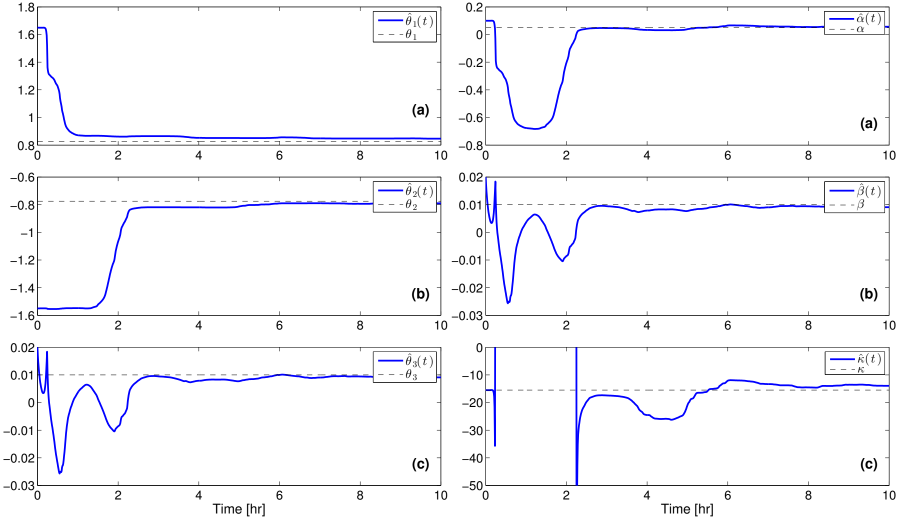
$$P(t) = \frac{\overline{P}}{\eta}\int_0^1 u(x,t)dx$$

Assumptions:

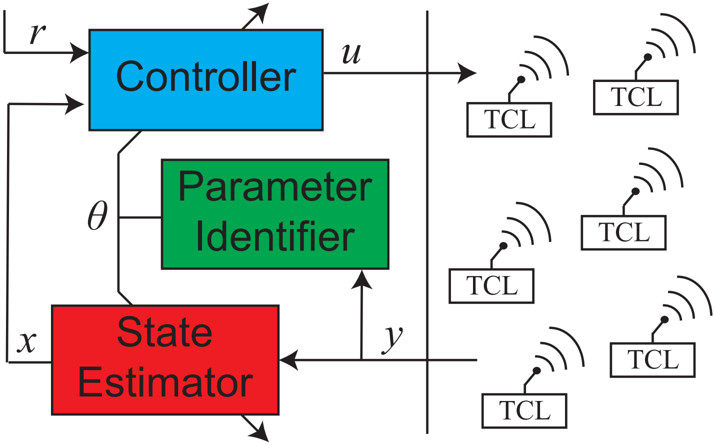
1. Aggregate Power $P(t)$ is measured
2. No. of TCLs switching $u(0,t), u(1,t), u_x(0,t), u_x(1,t)$ is measured

Simulations

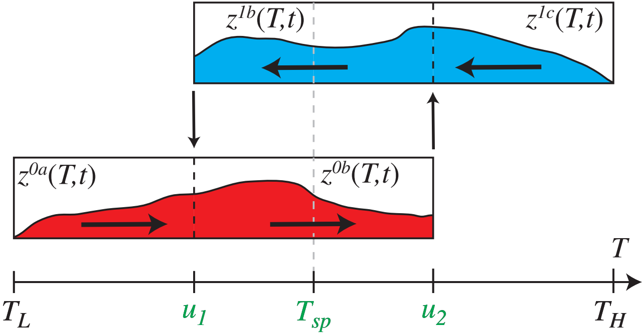
Identified from Population of 1,000 Heterogeneous TCLs



Feedback Control System



Set-point / Deadband Control



$$
\begin{aligned}
z_t^{1j}(T,t) &= \alpha\lambda(T) z_T^{1j}(T,t) + \alpha z^{1j}(T,t), \qquad j \in \{b,c\} \\
z_t^{0j}(T,t) &= -\alpha\mu(T) z_T^{0j}(T,t) + \alpha z^{0j}(T,t), \qquad j \in \{a,b\}
\end{aligned}
$$

with boundary conditions

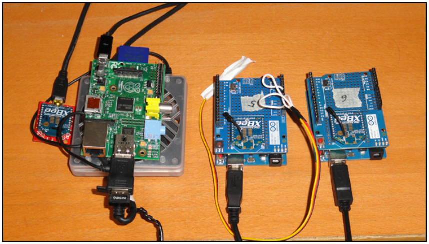
$$
\begin{aligned}
&z^{0a}(T_L,t) = 0, && z^{0b}(u_1,t) = z^{0a}(u_1,t) + z^{1b}(u_1,t), \\
&z^{1b}(u_2,t) = z^{1c}(u_2,t) + z^{0b}(u_2,t), && z^{1c}(T_H,t) = 0
\end{aligned}
$$

UC San Diego Campus: A Living Laboratory

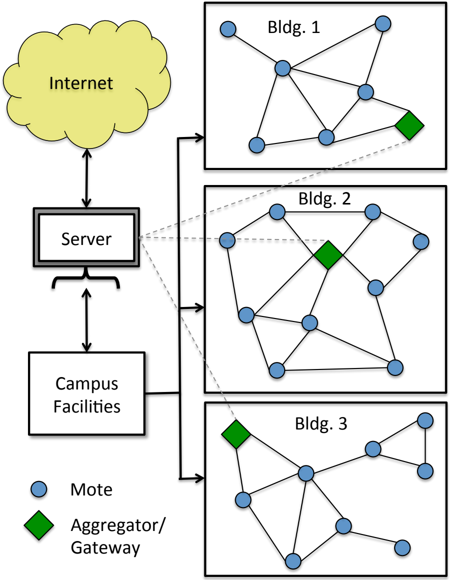
UC San Diego Campus: A Living Laboratory

Goal: DR for Bldg Energy Mgmt

1. Deploy wireless sensor network
2. Model/estimator verification
3. Control design
4. Campus implementation



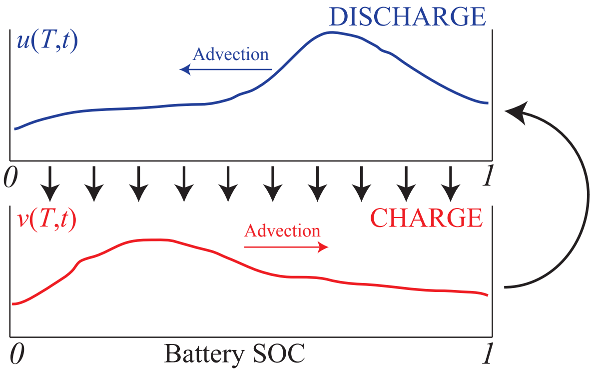
Aggregator (Raspberry Pi) & Sensor Nodes (Arduino)



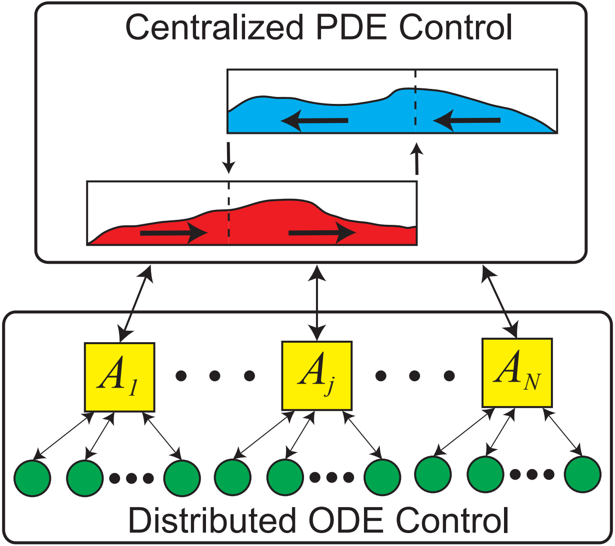
Modeling Aggregated PEVs

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



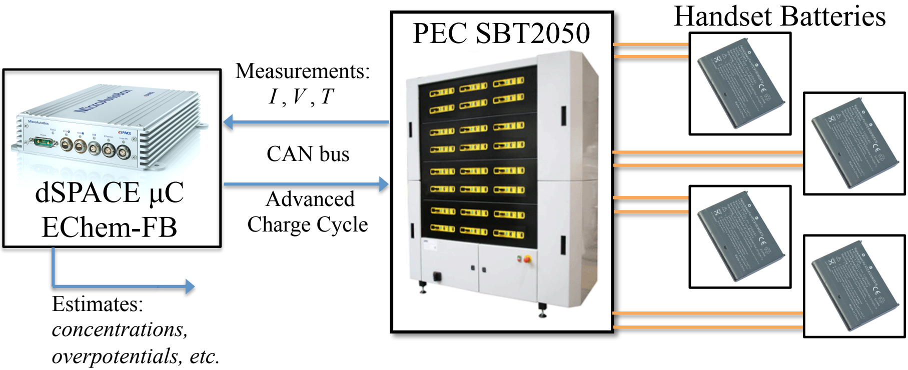
Hierarchical Control



Outline

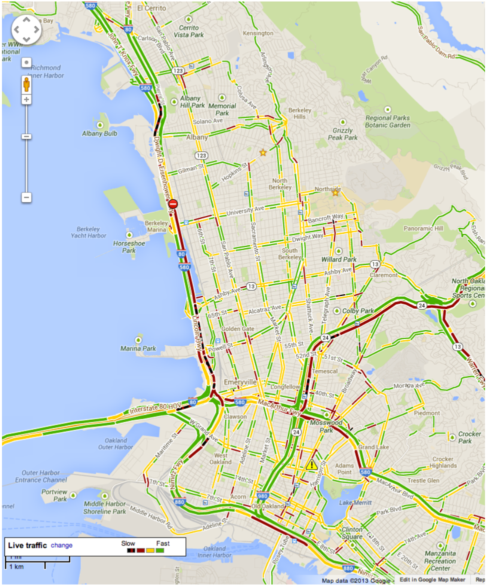
1. Electrochemistry-based Battery Controls
2. Demand Response of TCLs
3. Coming Soon...

Fast Charging



Motivation in Mobile Communication:
6.7B subscription accounts, 5.2B handsets in use,
1.7B sold worldwide in 2012

Optimize PHEV Energy Management w/ Real-time Traffic Data



$\rightarrow$

CE 186

DESIGN OF CYBER-PHYSICAL SYSTEMS

Spring 2014: Mon & Wed 2-4

Topics Include:

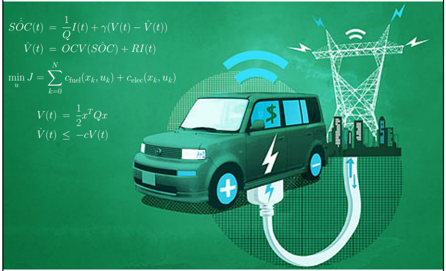
- Energy Management and Power Systems
- Vehicle-to-Grid and Battery Models
- Internet-based Systems
- Data Collection and Analysis

CE 290:002

ENERGY SYSTEMS & CONTROL

Spring 2014: MWF 10-11

Prof. Scott Moura



Topics Include:

- Energy Storage & Renewables
- Electrified Transportation
- State estimation
- Optimal control

Energy, Controls, and Applications Lab (eCAL)

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