Estimation of Distributed Parameter Systems with Applications to Building Energy and Vehicle Electrification

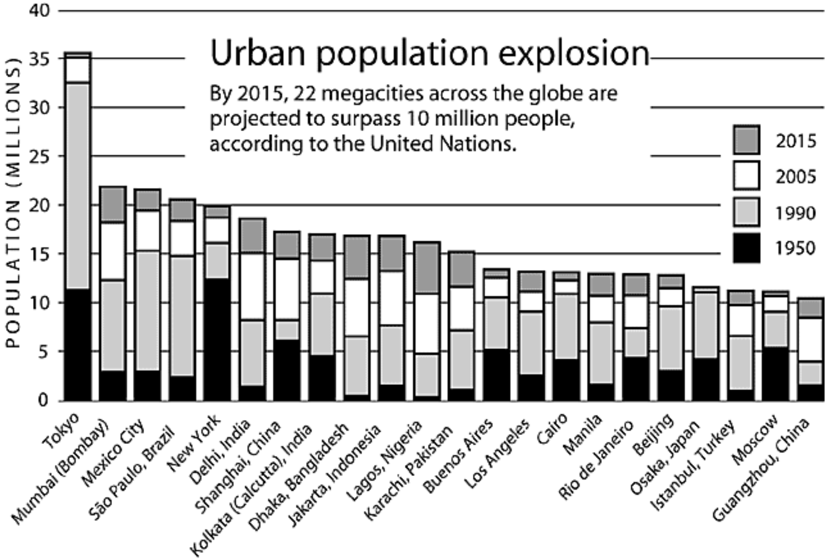
Scott Moura, Ph.D.

UC President's Postdoctoral Fellow
Cymer Center for Control Systems and Dynamics
UC San Diego

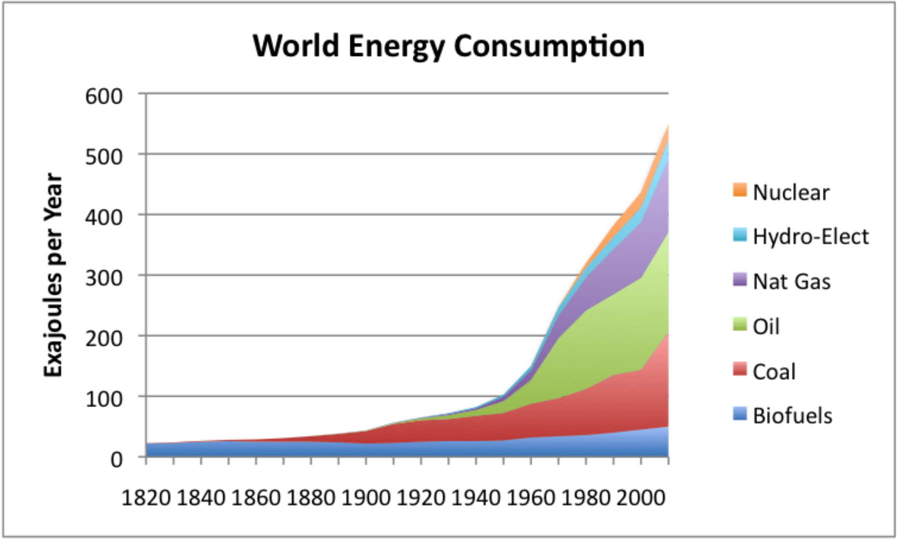
February 7, 2013

Core Philosophy:

$$\text{(Mathematical models of physical phenomena)}$$
$$+ \text{ (novel system \& control tools)}$$
$$= \text{ (transformative societal advancements)}$$



Source: United Nations, DESA, Population Division. World Urbanization Prospects.

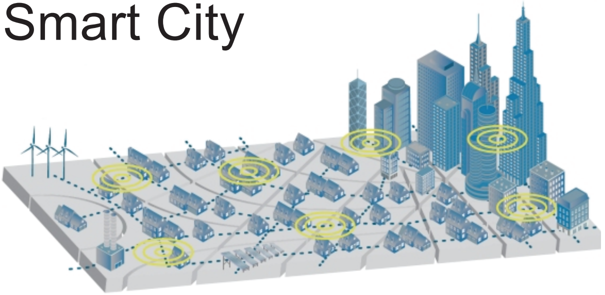


Source: Vaclav Smil Estimates from Energy Transitions

Photo from Superbowl

Photo from Superbowl

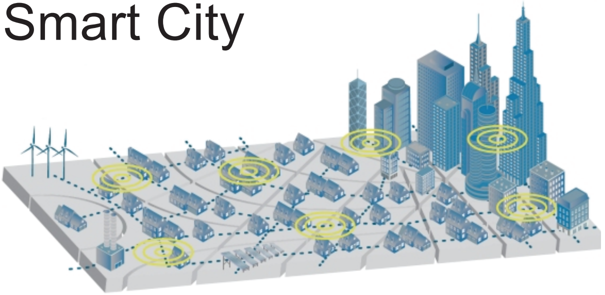
Smart City



- Mobility
- Energy
- Health
- Economics
- Structures
- Government

Categories adopted from: Giffinger, Rudolf; Christian Fertner, Hans Kramar, Robert Kalasek, Nataša Pichler-Milanovic, Evert Meijers (2007). “Smart cities - Ranking of European medium-sized cities.”

Smart City



- Mobility
- Energy
- Health
- Economics
- Structures
- Government

Categories adopted from: Giffinger, Rudolf; Christian Fertner, Hans Kramar, Robert Kalasek, Nataša Pichler-Milanovic, Evert Meijers (2007). “Smart cities - Ranking of European medium-sized cities.”

Key Objectives

Decrease energy waste	Integrate renewables
$\Downarrow$	$\Downarrow$
Intelligent energy management	Energy storage, e.g. batteries

Key Objectives

Decrease energy waste	Integrate renewables
$\Downarrow$	$\Downarrow$
Intelligent energy management	Energy storage, e.g. batteries

Outline

1. Modeling and Estimation for Building Energy
   - Modeling Aggregations via PDEs
   - Estimation - looking inside w/ Models, Meas., and Math
2. Vehicle to Grid Integration
3. Batteries
4. Future

Outline

1. Modeling and Estimation for Building Energy
   - Modeling Aggregations via PDEs
   - Estimation - looking inside w/ Models, Meas., and Math
2. Vehicle to Grid Integration
3. Batteries
4. Future

Why Buildings?

U.S. buildings produce

- 48% of carbon emissions

U.S. buildings consume

- 39% of total energy
- 71% of electricity
- 54% of natural gas

The Building Energy Problem

Needs: (1) Reduce energy waste, (2) sustainable and resilient infrastructure

The Building Energy Problem

Needs: (1) Reduce energy waste, (2) sustainable and resilient infrastructure

Obstacle: Scalability, sensing/control infrastructure

The Building Energy Problem

Needs: (1) Reduce energy waste, (2) sustainable and resilient infrastructure

Obstacle: Scalability, sensing/control infrastructure

Definition (Thermostatically Controlled Loads):
Systems controlled by on-off actuation, e.g. heated/cooled spaces in buildings

The Building Energy Problem

Needs: (1) Reduce energy waste, (2) sustainable and resilient infrastructure

Obstacle: Scalability, sensing/control infrastructure

Definition (Thermostatically Controlled Loads):
Systems controlled by on-off actuation, e.g. heated/cooled spaces in buildings

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

The Building Energy Problem

Needs: (1) Reduce energy waste, (2) sustainable and resilient infrastructure

Obstacle: Scalability, sensing/control infrastructure

Definition (Thermostatically Controlled Loads):
Systems controlled by on-off actuation, e.g. heated/cooled spaces in buildings

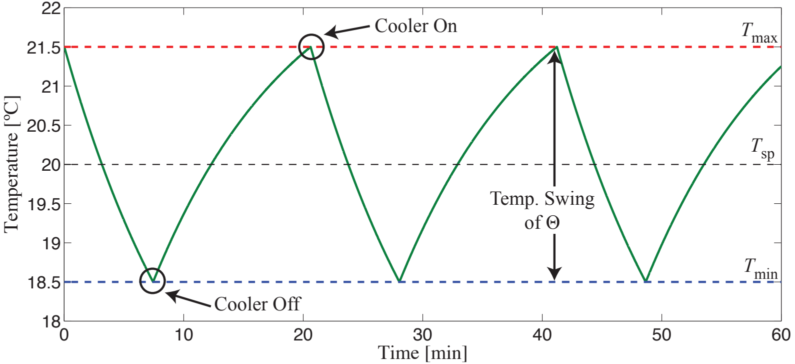
Some Interesting Facts

Thermostatically Controlled Loads (TCLs)	50% of U.S. electricity consumption is TCLs 11% of thermostats are programmed Comfort is loosely coupled with control

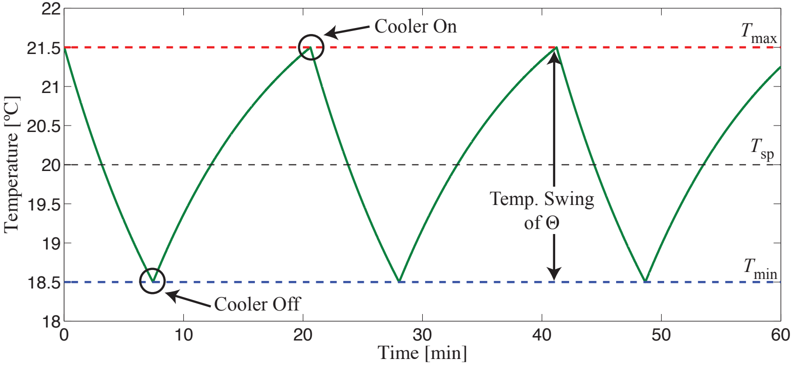
The Punchline

Exploit flexibility of TCLs to decrease energy waste

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

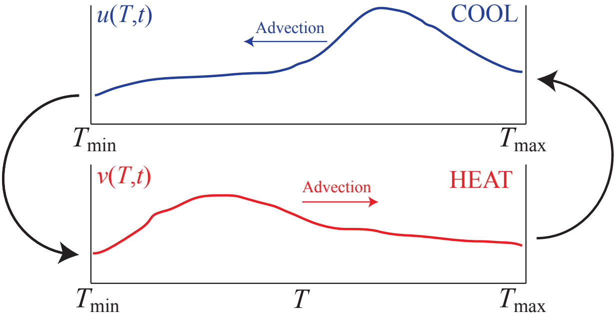
Main Idea: Convert 1000+ ODEs into two coupled linear PDEs

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

Modeling Aggregated TCLs

Main Idea: Convert 1000+ ODEs into 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 TCLs

Main Idea: Convert 1000+ ODEs into 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

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

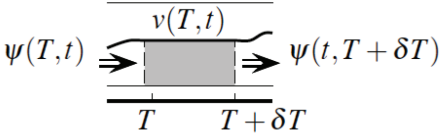
Main Idea: Convert 1000+ ODEs into two coupled linear PDEs

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

Flux of TCLs in HEAT state:
#TCLs / sec

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

Control volume:



Modeling Aggregated TCLs

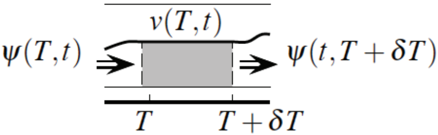
Main Idea: Convert 1000+ ODEs into two coupled linear PDEs

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

Flux of TCLs in HEAT state:
#TCLs / sec

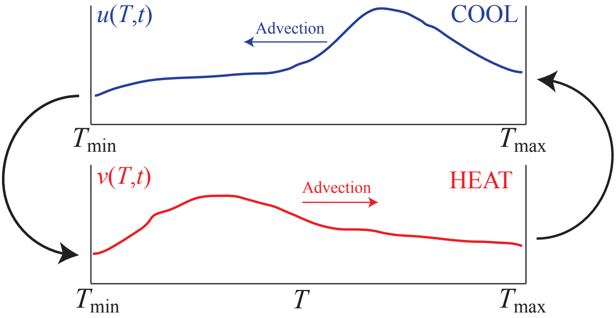
$$\psi(T,t) = v(T,t)\frac{dT}{dt}(t) = \frac{1}{RC}\left[T_\infty - T(t)\right] v(T,t)$$

Control volume:

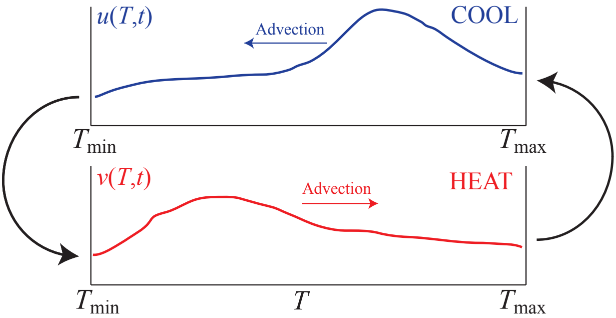


$$\begin{aligned}
\frac{\partial v}{\partial t}(T,t) &= \lim_{\delta T \to 0}\left[\frac{\psi(T+\delta T,t) - \psi(T,t)}{\delta T}\right] \\
&= \frac{\partial \psi}{\partial T}(T,t) \\
&= -\frac{1}{RC}\left[T_\infty - T(t)\right]\frac{\partial v}{\partial T}(T,t) + \frac{1}{RC} v(T,t)
\end{aligned}$$

PDE Model of Aggregated TCLs



PDE Model of Aggregated TCLs



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

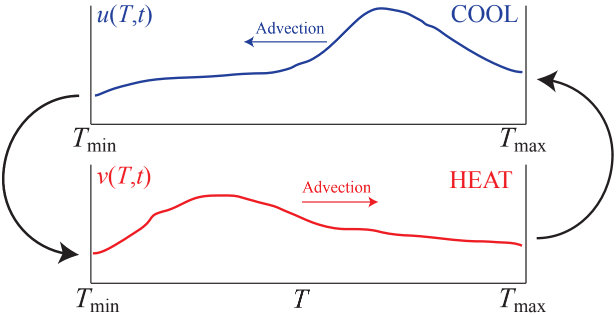
$$v_t(T,t) = -\alpha\mu(T)v_T(T,t) + \alpha v(T,t)$$

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

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

Video of 1,000 TCLs

PDE Model of Aggregated TCLs



$$u_t(T,t) = \alpha\lambda(T)u_T(T,t) + \alpha u(T,t)$$
$$v_t(T,t) = -\alpha\mu(T)v_T(T,t) + \alpha v(T,t)$$
$$u(T_{\max},t) = q_1 v(T_{\max},t)$$
$$v(T_{\min},t) = q_2 u(T_{\min},t)$$

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

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

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

Modeling Heterogeneous Aggregated TCLs

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

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

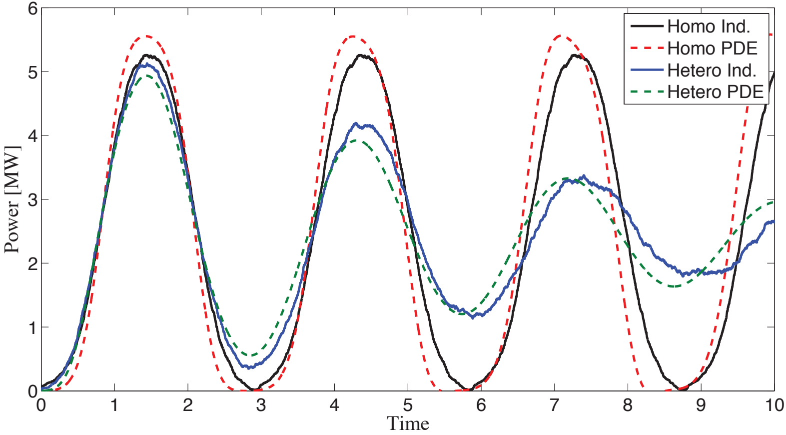
Proposition: The total number of TCLs is conserved over time.

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

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

Video Evolution of Heterogeneous PDE

Model Comparison



The State Estimation Problem

Question: Possible to monitor TCLs with minimal sensing infrastructure?

The State Estimation Problem

Question: Possible to monitor TCLs with minimal sensing infrastructure?

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

The State Estimation Problem

Question: Possible to monitor TCLs with minimal sensing infrastructure?

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

Problem Statement

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

The State Estimation Problem

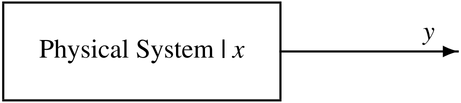
Question: Possible to monitor TCLs with minimal sensing infrastructure?

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

Problem Statement

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

Intro to Estimation



The State Estimation Problem

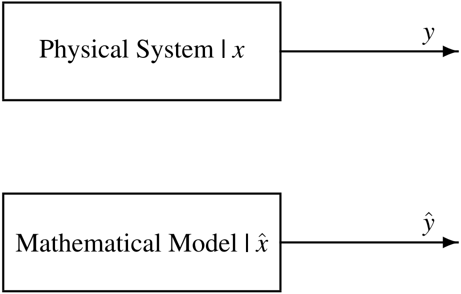
Question: Possible to monitor TCLs with minimal sensing infrastructure?

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

Problem Statement

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

Intro to Estimation



The State Estimation Problem

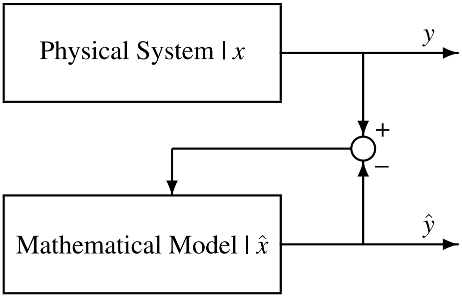
Question: Possible to monitor TCLs with minimal sensing infrastructure?

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

Problem Statement

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

Intro to Estimation



The State Estimation Problem

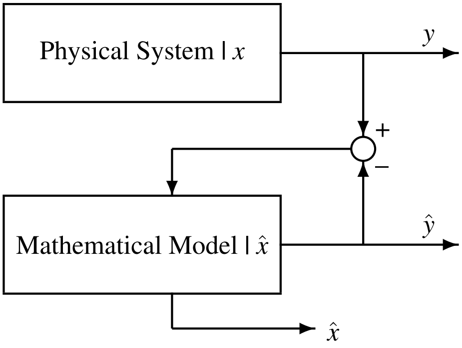
Question: Possible to monitor TCLs with minimal sensing infrastructure?

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

Problem Statement

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

Intro to Estimation



PDE State Estimator

Heterogeneous PDE Model: (u, v)

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

PDE State Estimator

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

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

PDE State Estimator

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

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

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

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

Lyapunov Stability Analysis

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

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

The time derivative along the solution trajectories

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

Lyapunov Stability Analysis

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

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

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

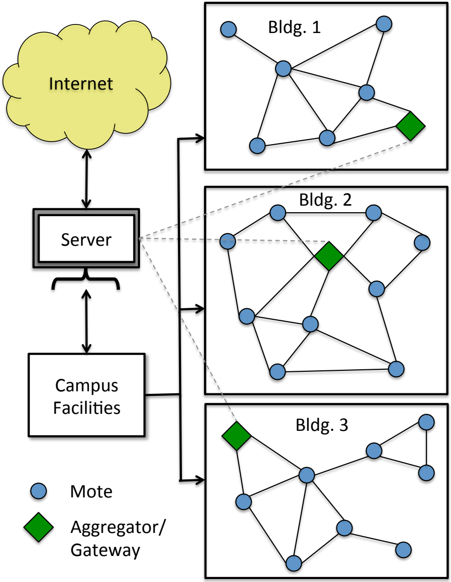
Key point: Converges to true distribution, using only HVAC on/off signals.

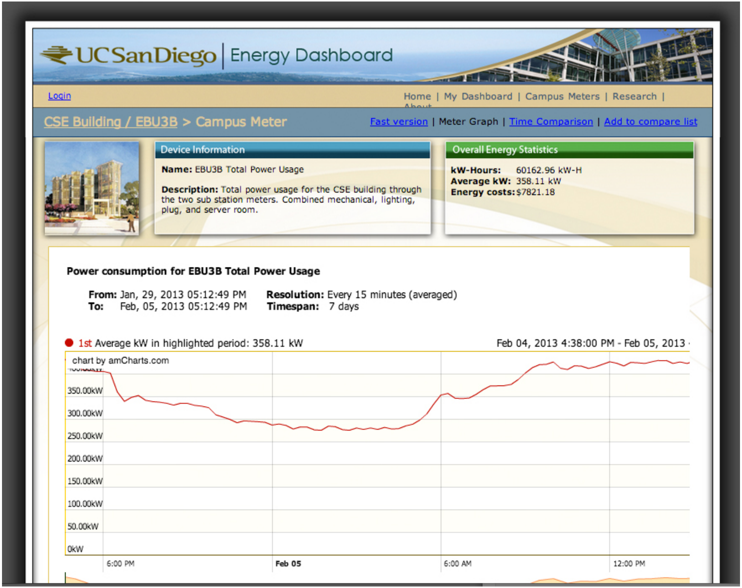
UCSD Campus: A Living Laboratory

Goal: Smart Campus

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

Libelium Waspmotes and Meshlium Gateway





energy.ucsd.edu

Fuse data from Dr. Yuvraj Agarwal's Energy Dashboard project

Main Contributions

1. Convert 1,000+ ODEs into two PDEs
    - Scalable
    - Elegant
    - Facilitates analysis and algorithm design
2. Monitor TCL population w/ min. sensing via boundary state estimation
    - Scalable
    - Reduces cost
    - Alleviates communication bandwidth req's

Outline

1. Modeling and Estimation for Building Energy
   - Modeling Aggregations via PDEs
   - Estimation - looking inside w/ Models, Meas., and Math

2. Vehicle to Grid Integration

3. Batteries

4. Future

The Vehicle-to-Grid (V2G) Integration Problem

Needs: Resilient and sustainable energy/transportation infrastructure

The Vehicle-to-Grid (V2G) Integration Problem

Needs: Resilient and sustainable energy/transportation infrastructure

Obstacle: Unprecedented constraints and demands

The Vehicle-to-Grid (V2G) Integration Problem

Needs: Resilient and sustainable energy/transportation infrastructure

Obstacle: Unprecedented constraints and demands

Some Interesting Facts

Plug-in Electric Vehicles (PEVs)	Potentially dispatchable loads “carbitrage” opportunity Firm variable renewables

The Vehicle-to-Grid (V2G) Integration Problem

Needs: Resilient and sustainable energy/transportation infrastructure

Obstacle: Unprecedented constraints and demands

Some Interesting Facts

Plug-in Electric Vehicles (PEVs)	
	Potentially dispatchable loads
	“carbitrage” opportunity
	Firm variable renewables

The Punchline

Exploit flexibility of PEV charging to enhance efficiency across infrastructures

Modeling Aggregated PEVs

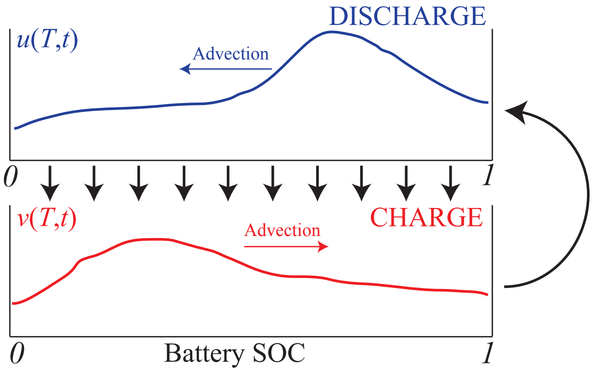
Main Idea: Mathematically model as coupled linear PDEs

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

Modeling Aggregated PEVs

Main Idea: Mathematically model as coupled linear PDEs

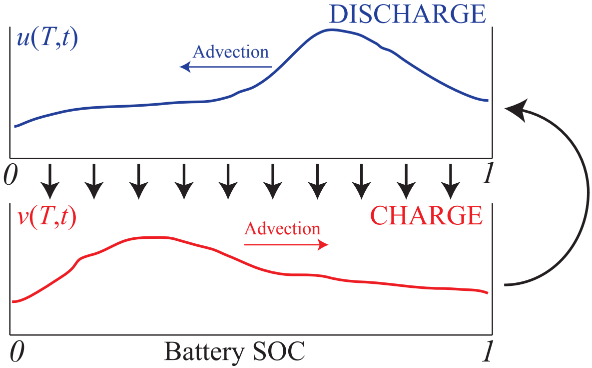
$u(T,t)$	# PEVs / SOC, in DISCHARGE state, @ SOC x, time t
$v(T,t)$	# PEVs / SOC, in CHARGE state, @ SOC x, time t



Modeling Aggregated PEVs

Main Idea: Mathematically model as coupled linear PDEs

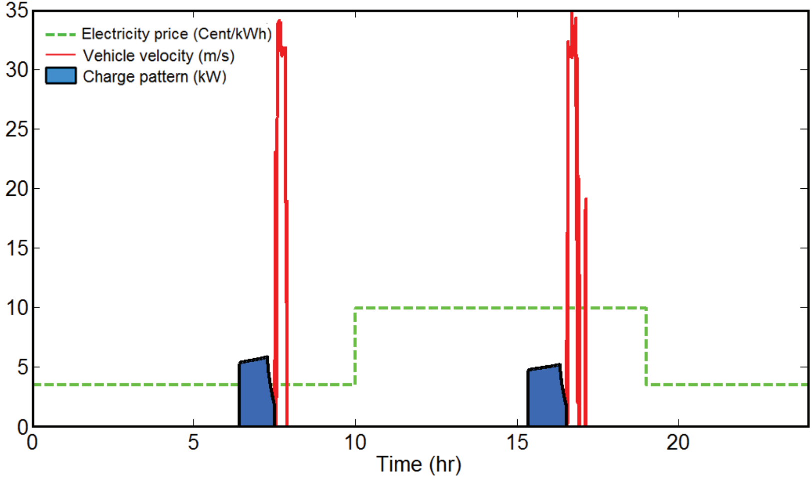
$u(T,t)$	# PEVs / SOC, in DISCHARGE state, @ SOC x, time t
$v(T,t)$	# PEVs / SOC, in CHARGE state, @ SOC x, time t



Open Questions: Modeling, state estimation, control/optimization, implementation

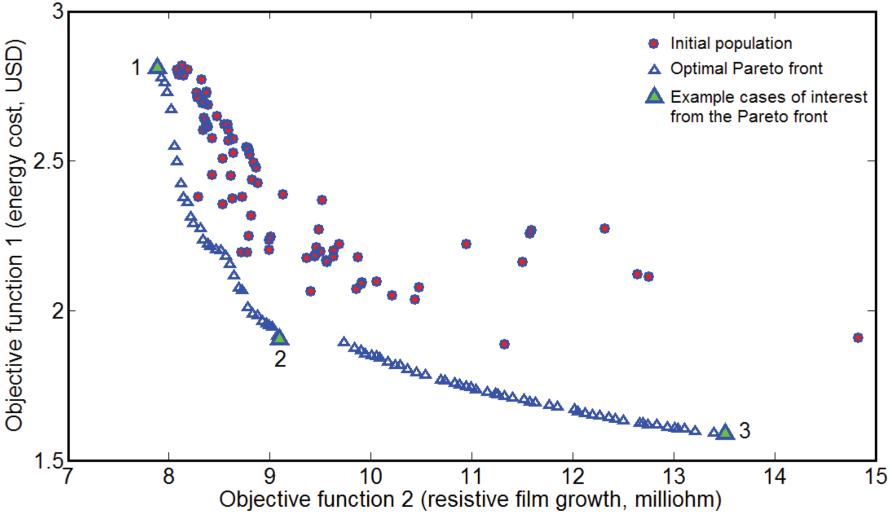
When to charge PEVs?

Research Question:	When to charge PEV's to maximize consumer-side benefits?
Objectives:	Fuel & electricity cost, battery health
Decision variables:	When, how long, at what rate?



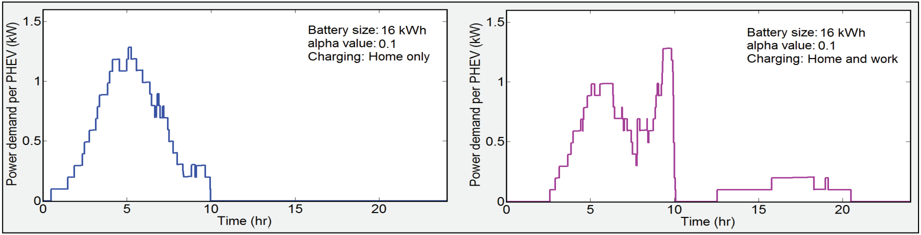
Multiobjective Optimization

Energy Cost vs. Battery Health



Infrastructure Req's?

Research Question:	Does charging at work lower peak loads?
Sensitivity to:	Fuel/electricity price, battery size, health vs. energy
Underlying Data:	NHTS Survey, UMTRI driving patterns



Solutions for Energy & Mobility Infrastructures

Decrease energy waste	Integrate sustainable resources
$\Downarrow$	$\Downarrow$
Intelligent energy management	Energy storage
(e.g., smart cities)	(e.g., batteries)

Solutions for Energy & Mobility Infrastructures

Decrease energy waste

$\Downarrow$

Intelligent energy management

(e.g., smart cities)

Integrate sustainable resources

$\Downarrow$

Energy storage

(e.g., batteries)

Outline

1. Modeling and Estimation for Building Energy
   - Modeling Aggregations via PDEs
   - Estimation - looking inside w/ Models, Meas., and Math
2. Vehicle to Grid Integration
3. Batteries
4. Future

The Battery Problem

Needs: Cheap, high energy, high power, long life

The Battery Problem

Needs: Cheap, high energy, high power, long life

Today's reality: Expensive, conservatively design/operated, die too quickly

The Battery Problem

Needs: Cheap, high energy, high power, long life

Today's reality: Expensive, conservatively design/operated, die too quickly

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

The Battery Problem

Needs: Cheap, high energy, high power, long life

Today's reality: Expensive, conservatively design/operated, die too quickly

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

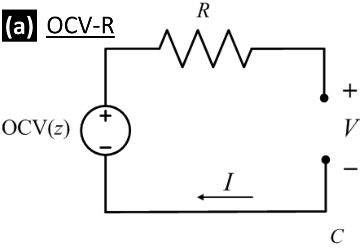
Two Solutions

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

Operate Batteries at their Physical Limits

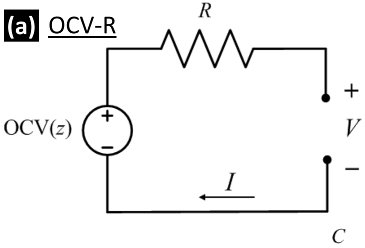
Equivalent Circuit Model

(a) OCV-R

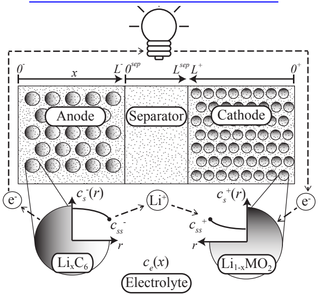


Operate Batteries at their Physical Limits

Equivalent Circuit Model

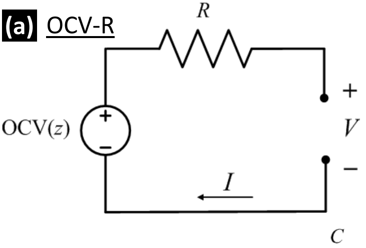


Electrochemical Model

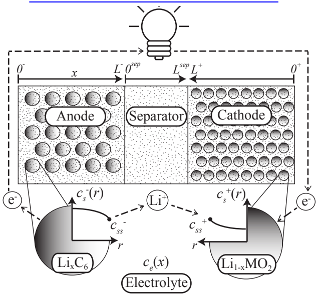


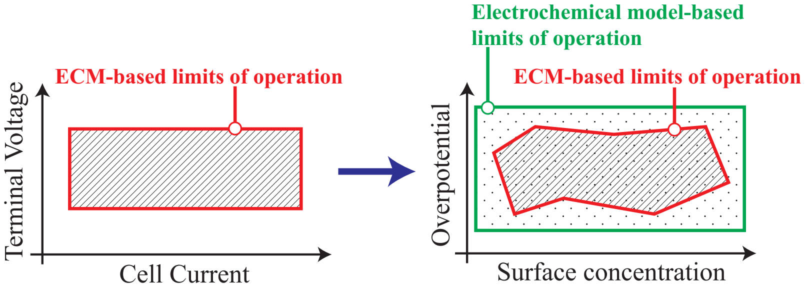
Operate Batteries at their Physical Limits

Equivalent Circuit Model

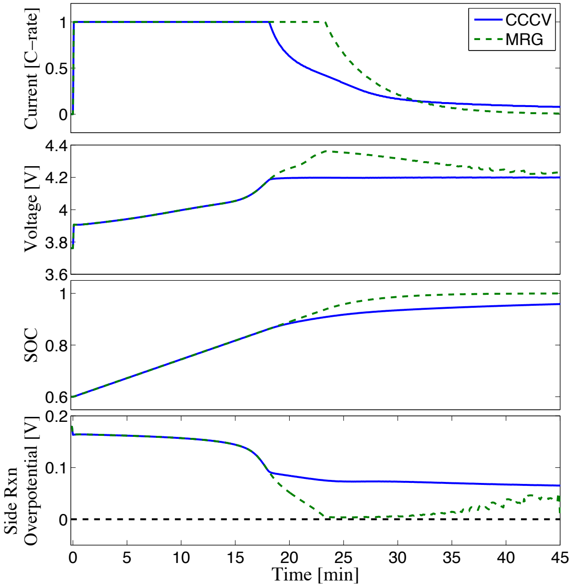


Electrochemical Model

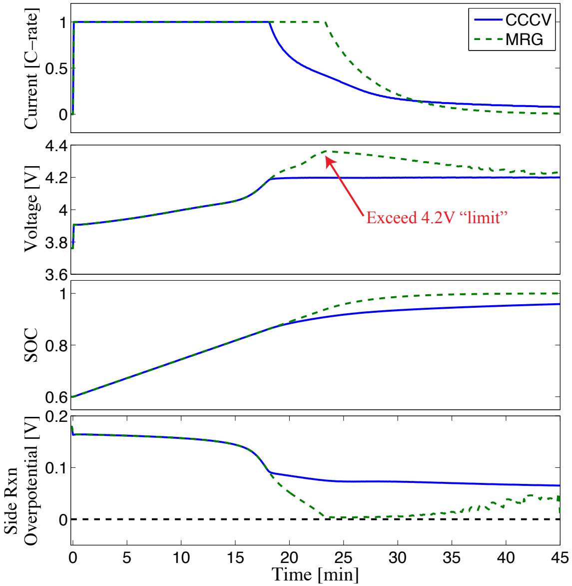




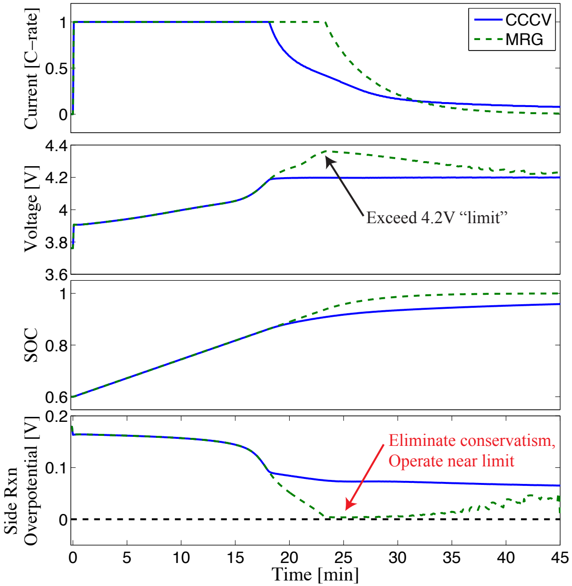
Operate at Limits. More energy, power, faster charge times.



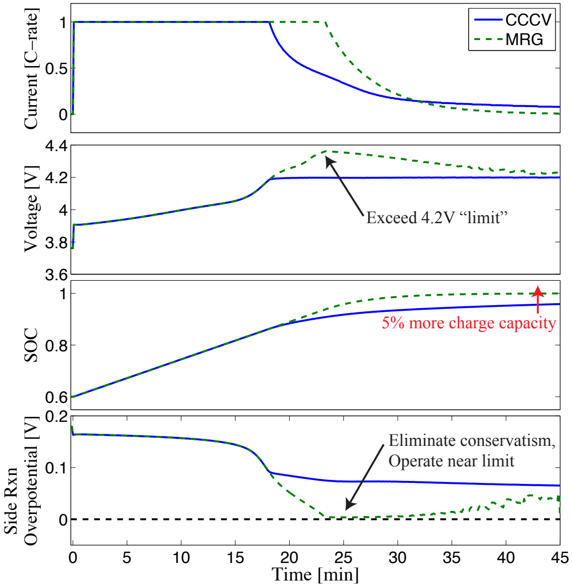
Operate at Limits. More energy, power, faster charge times.



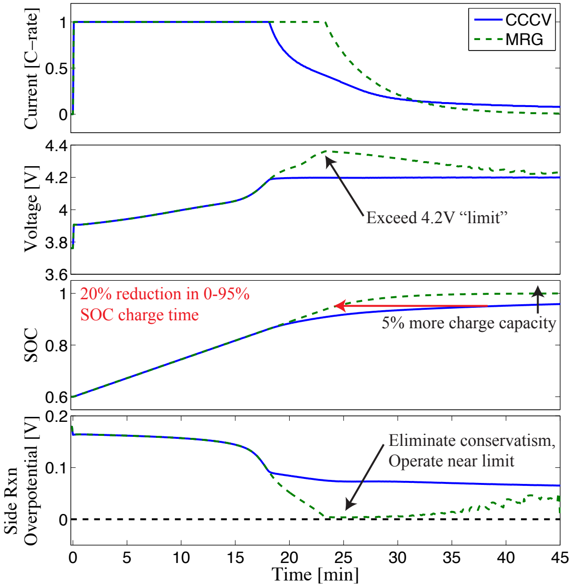
Operate at Limits. More energy, power, faster charge times.



Operate at Limits. More energy, power, faster charge times.



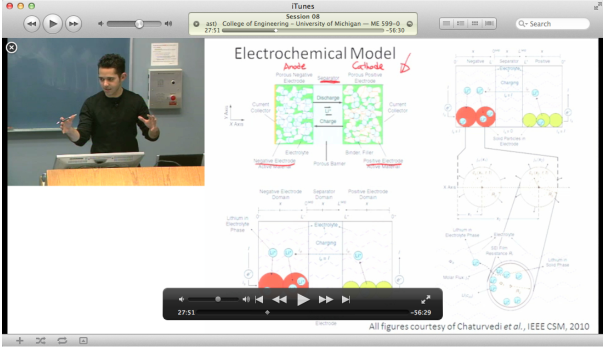
Operate at Limits. More energy, power, faster charge times.



Enrollment

- Winter 2010: 59 + 5 distance
- Winter 2011: 50 + 26 distance
- All majors across CoE

- Undergraduates
- Graduate students
- Professionals
  - Tesla Motors, General Motors, Roush, US Army



Main Contributions

State and parameter estimation
of physically meaningful variables via electrochemical models,
PDE estimation theory, and adaptive control.

Impact through education.

Outline

1. Modeling and Estimation for Building Energy
   - Modeling Aggregations via PDEs
   - Estimation - looking inside w/ Models, Meas., and Math
2. Vehicle to Grid Integration
3. Batteries
4. Future

Future: Cyber-Physical Building Systems

Vision: Fully automated and adaptive building energy management.

Open technical problems for Coupled Parabolic PDEs:
(1) Simultaneous State & Parameter Estimation

Future: Cyber-Physical Building Systems

Vision: Fully automated and adaptive building energy management.

Open technical problems for Coupled Parabolic PDEs:
(1) Simultaneous State & Parameter Estimation

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

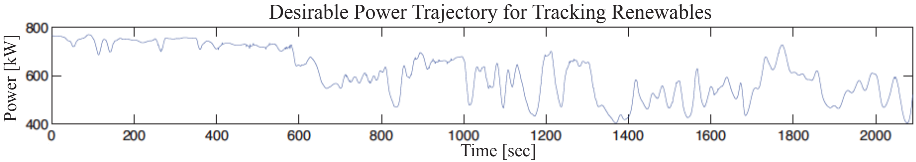
Future: Cyber-Physical Building Systems

Vision: Fully automated and adaptive building energy management.

Open technical problems for Coupled Parabolic PDEs:

(1) Simultaneous State & Parameter Estimation

(2) Reference Tracking Control via Temperature Setpoint Changes



Future: Cyber-Physical Building Systems

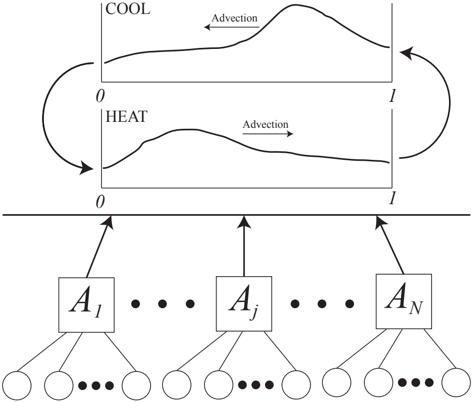
Vision: Fully automated and adaptive building energy management.

Open technical problems for Coupled Parabolic PDEs:

(1) Simultaneous State & Parameter Estimation

(2) Reference Tracking Control via Temperature Setpoint Changes

(3) Hierarchical Control Architecture



Future: Cyber-Physical Building Systems

Vision: Fully automated and adaptive building energy management.

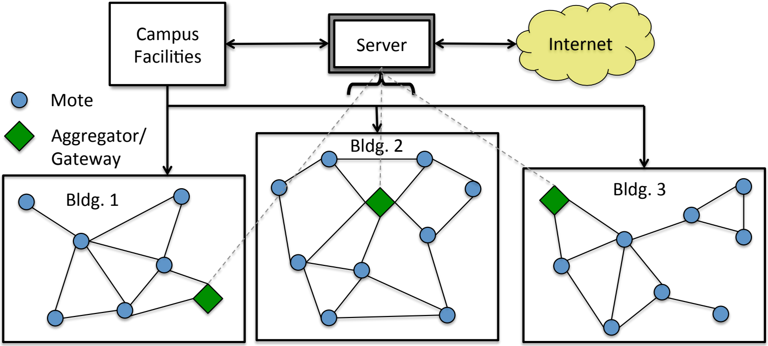
Open technical problems for Coupled Parabolic PDEs:

(1) Simultaneous State & Parameter Estimation

(2) Reference Tracking Control via Temperature Setpoint Changes

(3) Hierarchical Control Architecture

(4) UC Berkeley Campus Testbed



Future: Cyber-Physical Building Systems

Vision: Fully automated and adaptive building energy management.

Open technical problems for Coupled Parabolic PDEs:
(1) Simultaneous State & Parameter Estimation
(2) Reference Tracking Control via Temperature Setpoint Changes
(3) Hierarchical Control Architecture
(4) UC Berkeley Campus Testbed

Collaborators:

- Aalborg University, Denmark
- Nest Labs, Palo Alto
- Demand Response Research Center (LBL), Callaway (ERG), Auslander (ME), Poolla (ME), Varaiya (EECS)

Future: Cyber-Physical Building Systems

Vision: Fully automated and adaptive building energy management.

Open technical problems for Coupled Parabolic PDEs:
(1) Simultaneous State & Parameter Estimation
(2) Reference Tracking Control via Temperature Setpoint Changes
(3) Hierarchical Control Architecture
(4) UC Berkeley Campus Testbed

Collaborators:

- Aalborg University, Denmark
- Nest Labs, Palo Alto
- Demand Response Research Center (LBL), Callaway (ERG), Auslander (ME), Poolla (ME), Varaiya (EECS)

Funding:

- California Energy Commission
- NSF EPAS, CPS

Future: EV Urban Mobility

Goal: Solve range anxiety

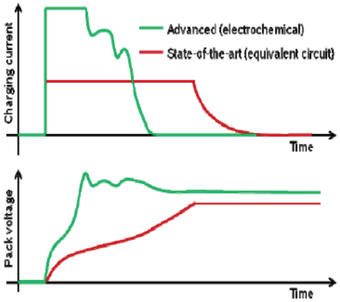
Key components:

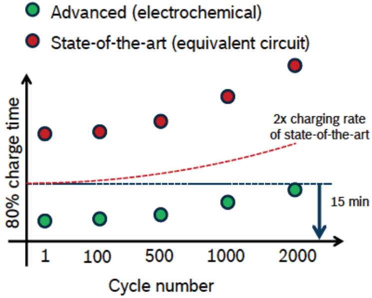
Future: EV Urban Mobility

Goal: Solve range anxiety

Key components:

(1) Fast-safe charging





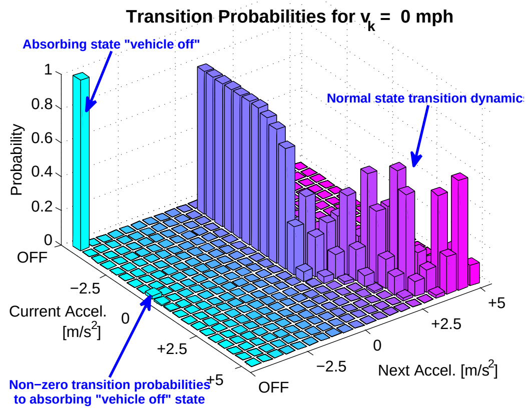
Goal: Solve range anxiety

Key components:

(1) Fast-safe charging

(2) Self-Learning Driving Patterns

Adaptive Markov chain model: $p_{ijm} = \Pr\left(a_{k+1} = j | a_k = i, v_k = m\right)$



Future: EV Urban Mobility

Goal: Solve range anxiety

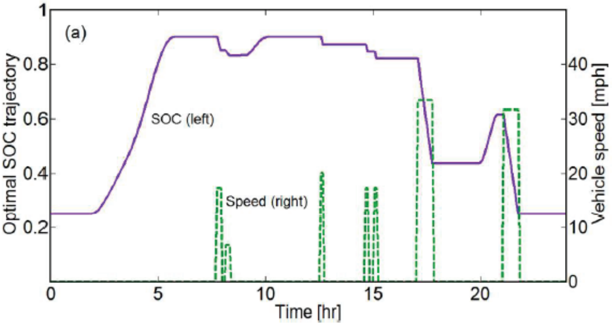
Key components:

(1) Fast-safe charging

(2) Self-Learning Driving Patterns

(3) Optimal EV Usage

- Satisfy range req.
- Max health, min energy consumption
- Grid interface for city-wide resilience



Future: EV Urban Mobility

Goal: Solve range anxiety

Key components:
(1) Fast-safe charging
(2) Self-Learning Driving Patterns
(3) Optimal EV Usage

Collaborators:

- Robert Bosch RTC, Palo Alto
- Optimal control of PDEs (Bayen)
- Electric mobility LCA & course development (ECIC program - Horvath)
- V2G integration, charging infrastructure (TSRC - Shaheen, Madanat)

Future: EV Urban Mobility

Goal: Solve range anxiety

Key components:
(1) Fast-safe charging
(2) Self-Learning Driving Patterns
(3) Optimal EV Usage

Collaborators:

- Robert Bosch RTC, Palo Alto
- Optimal control of PDEs (Bayen)
- Electric mobility LCA & course development (ECIC program - Horvath)
- V2G integration, charging infrastructure (TSRC - Shaheen, Madanat)

Funding:

- ARPA-E AMPED
- DoD HESM

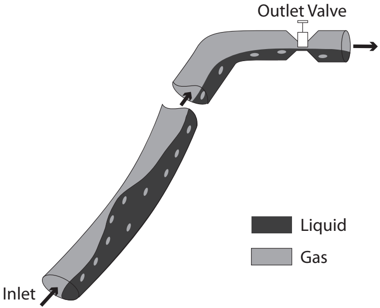
Future: Multiphase Flow of Oil Production Systems

Collaboration with CAS @ Ecole des Mines (di Meglio, Petit) and Statoil

Goal: Control slugging

Technical problem: Estimation & control of multiphase flow

$$\frac{\partial \zeta}{\partial t}(x,t) + A(\zeta)\frac{\partial \zeta}{\partial x}(x,t) = S(x)$$



Images courtesy of Florent di Meglio

Courses I could teach

Undergrad
CE 93 - Engineering Data Analysis
CE 155 - Transportation Systems Engineering

Graduate
CE 186 - Design of Cyber-Physical Systems
CE 200B - Numerical Methods for Environmental Flow Monitoring (Chow)
CE 268E - Civil Systems and the Environment (Horvath)
C291F - Control & Optimization of Distributed Parameter Systems (Bayen)

Control & Automation Laboratory (Cal) for Infrastructure Systems

Themes: Energy | Electrified mobility

Themes: Energy | Electrified mobility

Key Tools:

- PDE modeling
- Lyapunov stability
- Adaptive control
- Optimization

Control & Automation Laboratory (Cal) for Infrastructure Systems

Themes: Energy | Electrified mobility

Key Tools:

- PDE modeling
- Lyapunov stability
- Adaptive control
- Optimization

Balance

Theory/Computational	70%	30%	Experimental

Control & Automation Laboratory (Cal) for Infrastructure Systems

Themes: Energy | Electrified mobility

Key Tools:

- PDE modeling
- Lyapunov stability
- Adaptive control
- Optimization

Balance

Theory/Computational 70%	30% Experimental

Key Collaborations

Academia	Michigan, UC San Diego, Ecole des Mines, Aalborg Univ.
Industry	Bosch RTC, Nest Labs, Ford Motor Company

Control & Automation Laboratory (Cal) for Infrastructure Systems

Themes: Energy | Electrified mobility

Key Tools:

- PDE modeling
- Lyapunov stability
- Adaptive control
- Optimization

Balance

Theory/Computational 70%	30% Experimental

Key Collaborations

Academia	Michigan, UC San Diego, Ecole des Mines, Aalborg Univ.
Industry	Bosch RTC, Nest Labs, Ford Motor Company

Outreach, Diversity, and Inclusion

- Cal NERDS
- HES, BESSA, SWE
- SUPERB, UC LEADs

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