Modeling and Estimation of Demand Responsive Loads

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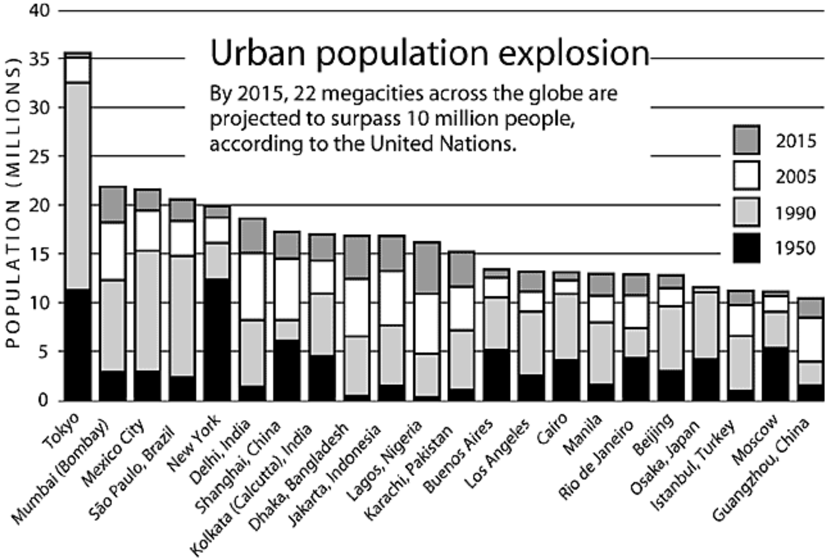
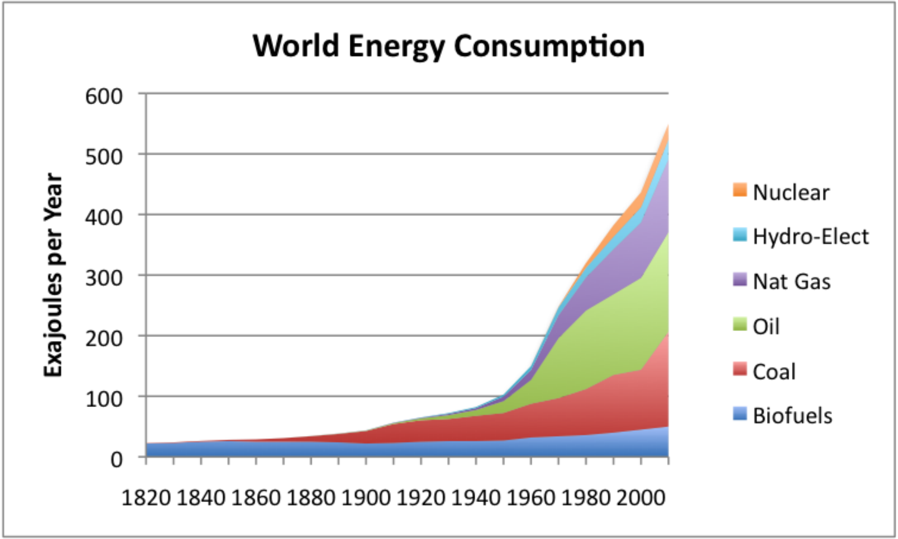
International Workshop on Smart City:
Control and Automation Perspectives

Hangzhou, China
August 28, 2013



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



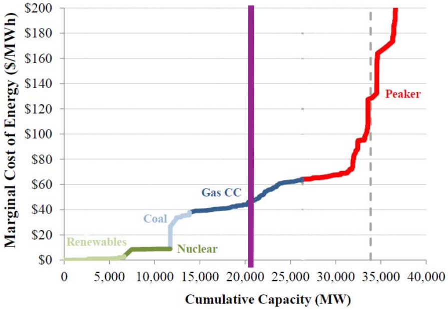
Source: Vaclav Smil Estimates from Energy Transitions

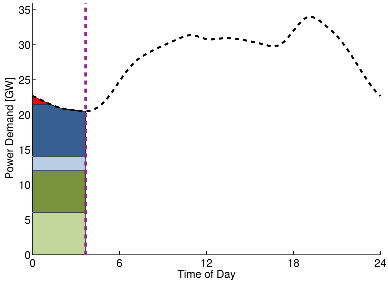
Integrating Renewables

Ambitious targets:

- CA: 33% renewables by 2020
- US: 20% wind penetration by 2030
- Denmark: 50% wind penetration by 2025
- China: 15% renewables by 2020

Power Market Supply/Demand

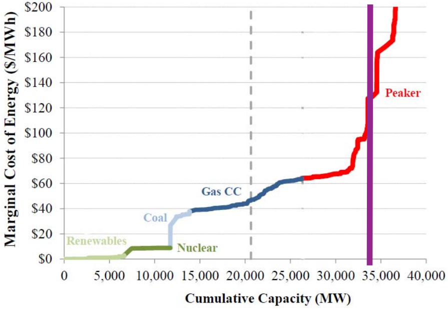




Supply

Demand

Power Market Supply/Demand



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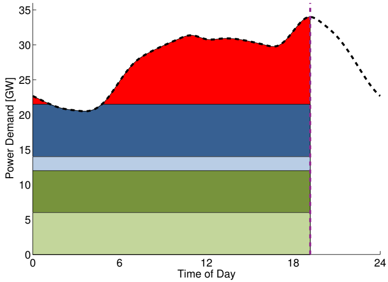
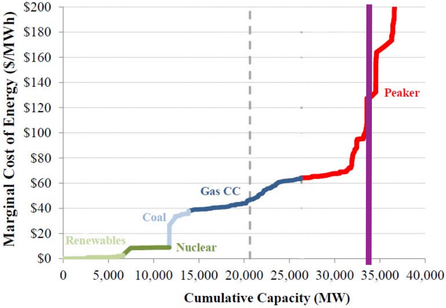
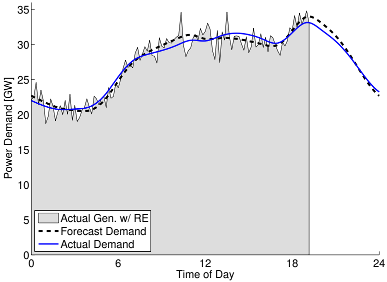


Demand

Power Market Supply/Demand

Reality: Renewables are variable!





Supply

Demand

The Cost of Renewables w/o doing something "SMART"

Increased variability is THE problem!

Assuming 33% RE penetration, and current practices,
the following reserve capacity must be added [Helman 2010]:

- Load following: 2.3 GW $\rightarrow$ 4.4 GW
- Regulation: 227 MW $\rightarrow$ 1.4 GW

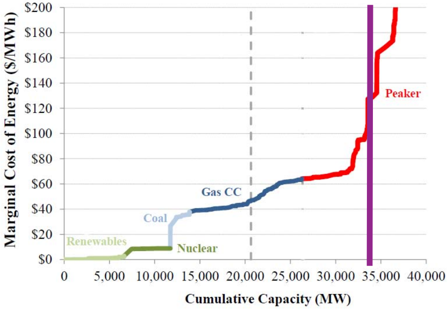
Added costs due to reserves at 15% renewable penetration

- $2.50 - $5 per MW of renewable generation [EWITS study, NREL, 2010]

Additional dirty and expensive reserves defeats benefits!

Power Market Supply/SMART Demand

Goal: Actual Demand with Demand Response (DR)



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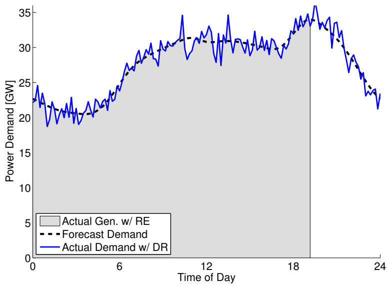

Demand

Outline

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The DR Problem

Needs: Monitor & actuate (very) large populations of flexible loads

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Definition (Thermostatically Controlled Loads):
Systems controlled by on-off actuation, e.g. HVAC, water heaters, freezers

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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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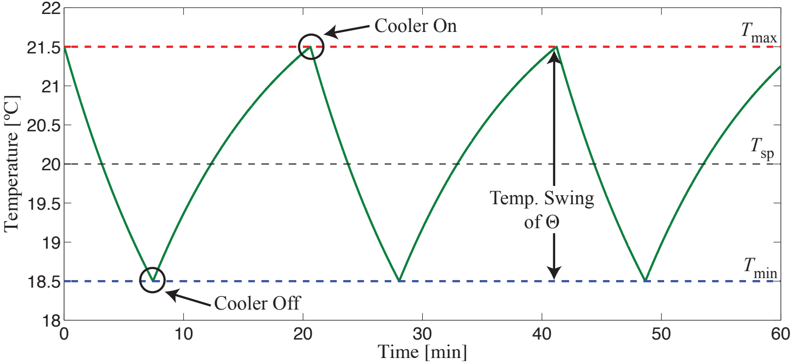
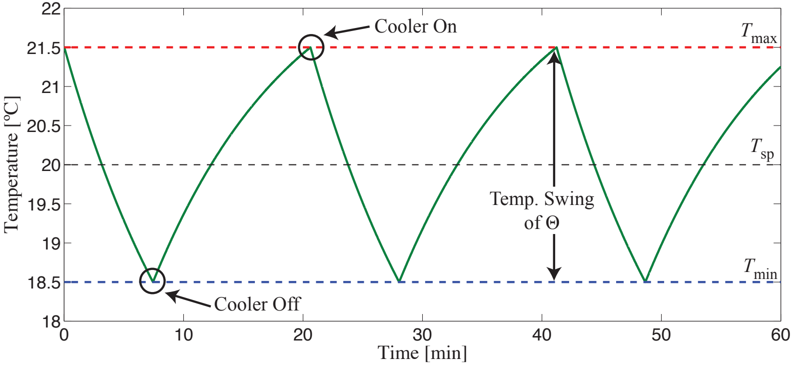
The Punchline

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

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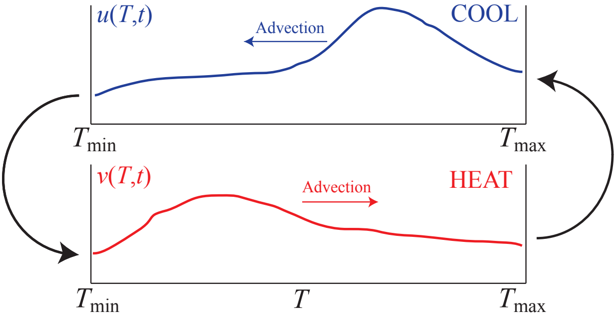

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Flux of TCLs in HEAT state:
#TCLs / sec

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

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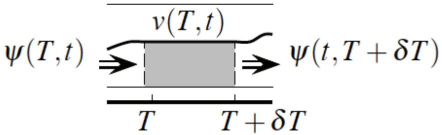
Control volume:



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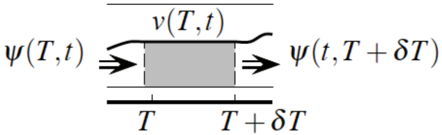
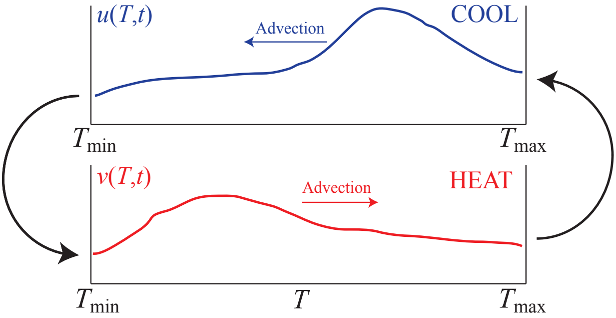


$$\begin{aligned}
\frac{\partial v}{\partial t}(T,t) &= \lim_{\delta T \to 0}\left[\frac{\psi(T+\delta T,t) - \psi(T,t)}{\delta T}\right] \\
&= \frac{\partial \psi}{\partial T}(T,t) \\
&= -\frac{1}{RC}\left[T_\infty - T(t)\right]\frac{\partial v}{\partial T}(T,t) + \frac{1}{RC} v(T,t)
\end{aligned}$$

PDE Model of Aggregated TCLs



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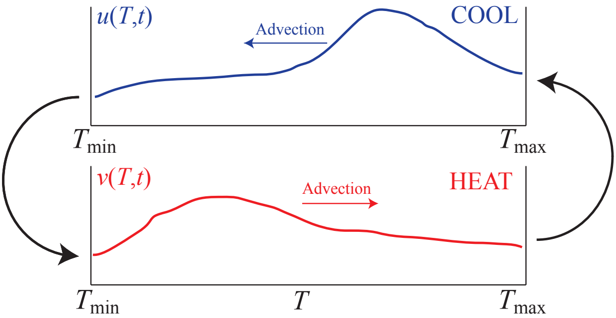

$$u_t(T,t) = \alpha\lambda(T)u_T(T,t) + \alpha u(T,t)$$
$$v_t(T,t) = -\alpha\mu(T)v_T(T,t) + \alpha v(T,t)$$
$$u(T_{\max},t) = q_1 v(T_{\max},t)$$
$$v(T_{\min},t) = q_2 u(T_{\min},t)$$

Video of 1,000 TCLs

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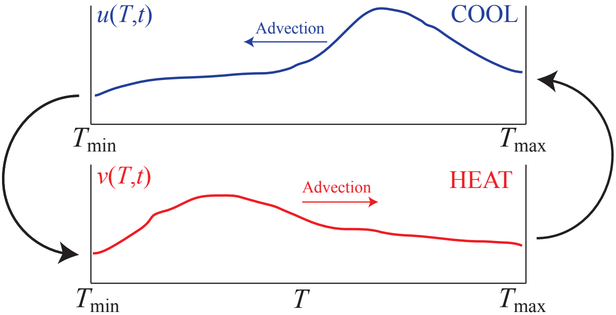

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Original Idea: Malhame and Chong, Trans. on Automatic Control (1985)

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

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

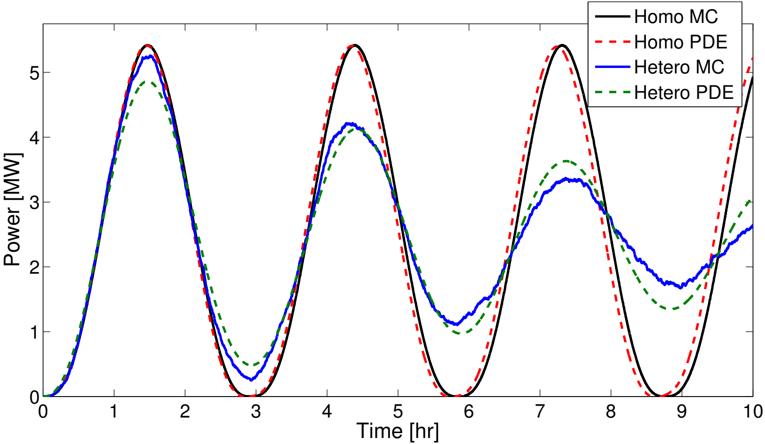
Proposition: The total number of TCLs is conserved over time.

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

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

Video Evolution of Heterogeneous PDE

Model Comparison



The State Estimation Problem

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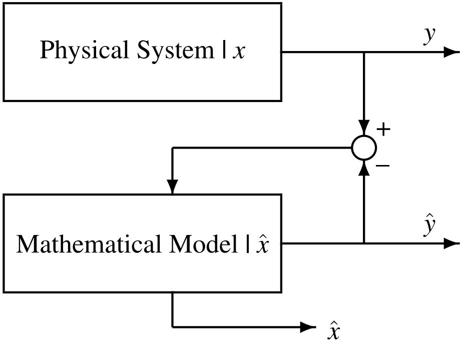
Problem Statement

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

Finite-dimensional system:



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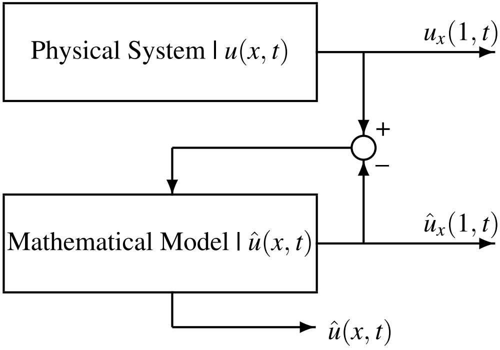

PDE State Estimator

Heterogeneous PDE Model: (u, v)

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

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

Measurements?

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

PDE State Estimator

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

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

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

PDE State Estimator

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

$$
\begin{aligned}
\tilde{u}_t(x,t) &= \alpha\lambda(x)\tilde{u}_x + \alpha\tilde{u} + \beta\tilde{u}_{xx} - p_1(x)\tilde{u}(0,t) \\
\tilde{u}_x(0,t) &= -p_{10}\tilde{u}(0,t) \\
\tilde{u}(1,t) &= 0
\end{aligned}
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\tilde{v}_x(1,t) &= -p_{20}\tilde{v}(1,t)
\end{aligned}$$

Goal: Design estimation gains:

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

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

Backstepping Observer Design

Error Dynamics: $\tilde{u}$

$$\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) \\
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Eliminate advection terms, "Gauge" Transformation

$$\xi(x,t) = \tilde{u}(x,t)e^{\frac{\alpha}{2\beta}\int_0^x \lambda(s)ds}$$

Backstepping Observer Design

Transformed error state: ξ

$$
\begin{aligned}
\xi_t(x,t) &= \beta\xi_{xx} + g(x)\xi - p_1^{\xi}(x)\xi(0,t) \\
\xi_x(0,t) &= p_{10}^{\xi}\xi(0,t) \\
\xi(1,t) &= 0
\end{aligned}
$$

$$
\begin{aligned}
g(x) &= \alpha\left[1 - \frac{\lambda'(x)}{2}\right] - \frac{\alpha^2\lambda^2(x)}{4\beta} \\
p_1^{\xi}(x) &= p_1(x)e^{\frac{\alpha}{2\beta}\int_0^x \lambda(s)ds} \\
p_{10}^{\xi} &= \frac{\alpha}{2\beta}\lambda(0) - p_{10}
\end{aligned}
$$

Backstepping Observer Design

Transformed error state: ξ

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\end{aligned}$$

Backstepping transformation

$$\xi(x,t) = w_1(x,t) - \int_0^x p(x,y) w_1(y,t) dy$$

Backstepping Observer Design

Transformed error state: ξ

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\end{aligned}$$

Backstepping transformation

$$\xi(x,t) = w_1(x,t) - \int_0^x p(x,y) w_1(y,t) dy$$

Target system: w_1, exp. stable in $\mathcal{L}^2$-norm

$$\begin{aligned}
w_{1t}(x,t) &= \beta w_{1xx}(x,t) - c_1 w_1(x,t), \qquad c_1 \geq 0 \\
w_{1x}(0,t) &= w_1(0,t) \\
w_1(1,t) &= 0
\end{aligned}$$

Backstepping Observer Design

Kernel PDE: $p(x, y)$

$$\begin{aligned} \beta p_{xx}(x,y) - \beta p_{yy}(x,y) &= -\left[c_1 + g(x)\right] p(x,y) \\ p(x,x) &= -\frac{1}{2\beta} \int_x^1 \left[c_1 + g(s)\right] ds \\ p(1,y) &= 0 \end{aligned}$$

Backstepping Observer Design

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p(1,y) &= 0
\end{aligned}$$

Estimation gains

$$\begin{aligned}
p_1^{\xi}(x) &= -\beta\left[p(x,0) + p_y(x,0)\right] \\
p_{10}^{\xi} &= 1 - p(0,0) \\
p_1(x) &= p_1^{\xi}(x) e^{-\frac{\alpha}{2\beta}\int_0^x \lambda(s) ds} \\
p_{10} &= \frac{\alpha}{2\beta}\lambda(0) - p_{10}^{\xi}
\end{aligned}$$

Video Evolution of PDE estimator

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

Parameter Identification

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

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

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

Algorithm #1: Power-based Identification [DSCC13]

- Assumes measurements of aggregate power consumption & B.C.'s

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$$u_x(0,t) = -v_x(0,t) \qquad v(0,t) = q_2 u(0,t)$$

$$u(1,t) = q_1 v(1,t) \qquad v_x(1,t) = -u_x(1,t)$$

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

Algorithm #1: Power-based Identification [DSCC13]

- Assumes measurements of aggregate power consumption & B.C.'s

Algorithm #2: Passive Identifier [IJC]

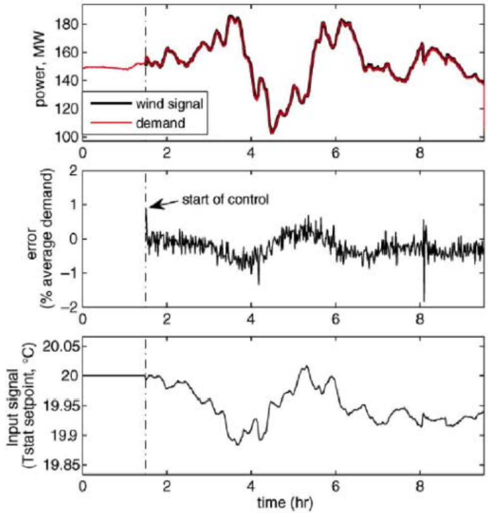
- Assumes full state measurements

Algorithm #3: Swapping Identifier [IJC]

- Assumes full state measurements

Output Regulation Problem

[Callaway, 2009]



- $P(t) \approx w(t)$
- Tracking error $\approx 1\%$
- Setpoint changes $\approx 0.1^\circ C$

UC San Diego Campus: A Living Laboratory

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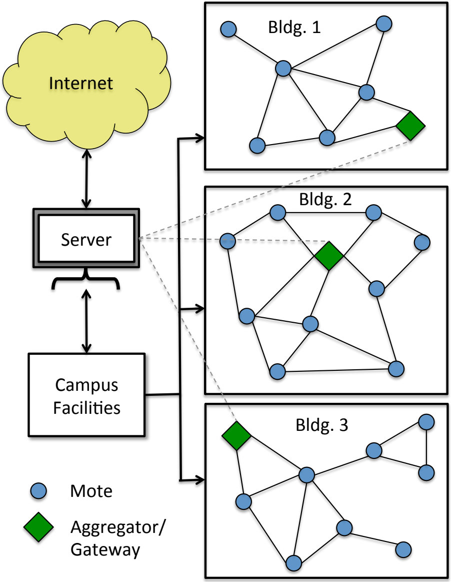
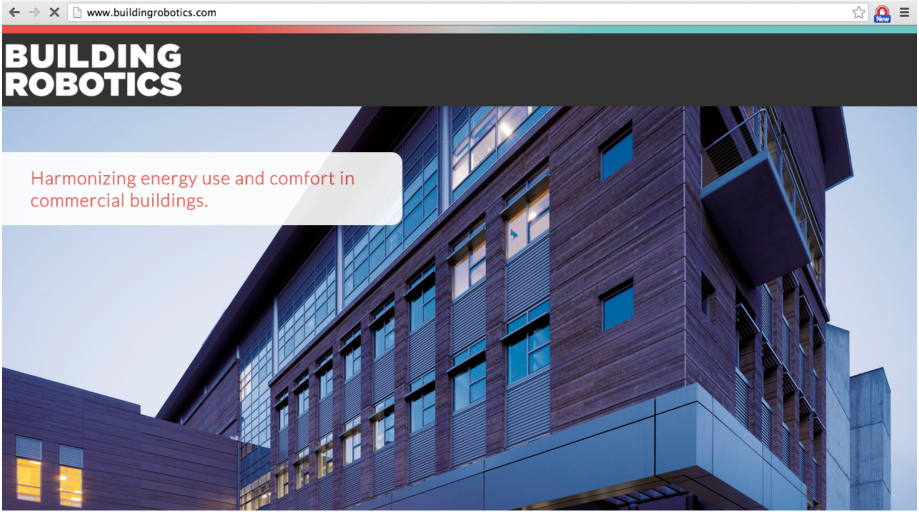
Goal: Exploit Flexible Loads in Bldgs

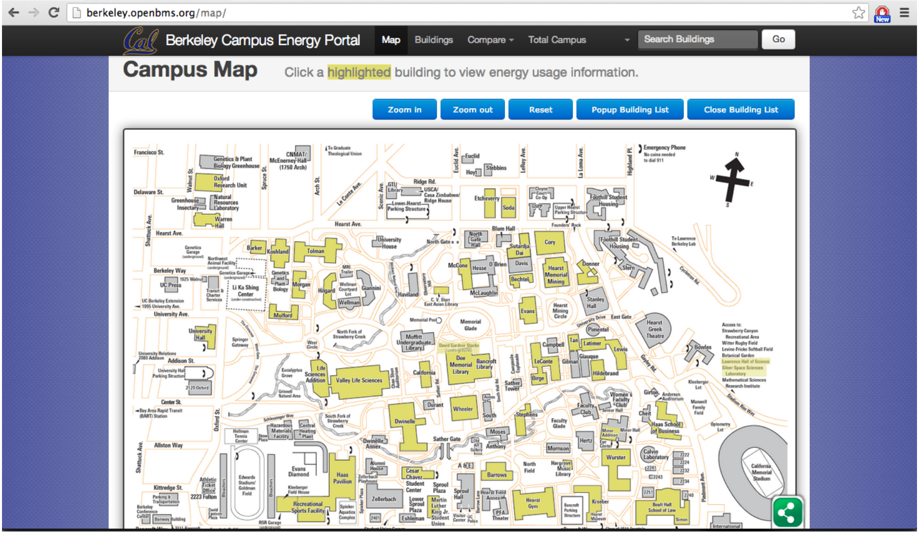
1. Deploy wireless sensor network
2. Model/estimator verification
3. Control design
4. Campus implementation

Libelium Waspmotes and Meshlium Gateway





Software platform for collecting building energy data
Prof. David Culler's Group | EECS @ UC Berkeley



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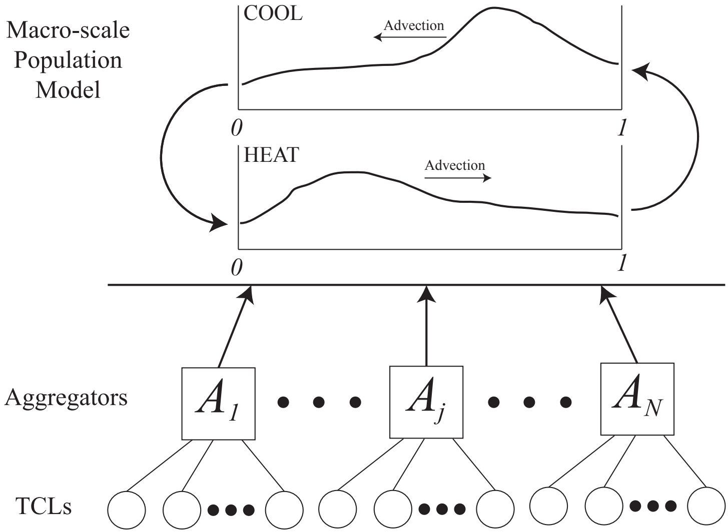
Hierarchical Control/Monitoring Structure



Outline

The PEV-Grid Integration Problem

Obstacle: PEVs impose unprecedented constraints and demands on grid

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Opportunities: (1) Mitigate PEV load; (2) Exploit online disturbed energy storage

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	"carbitrage" opportunity
	Firm variable renewables

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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

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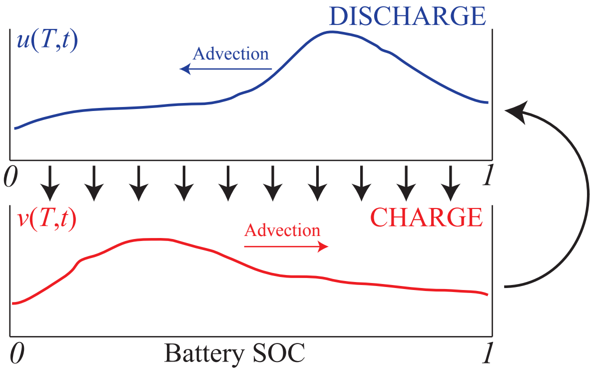

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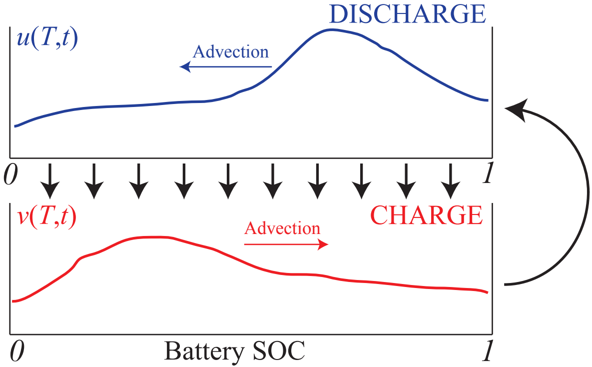
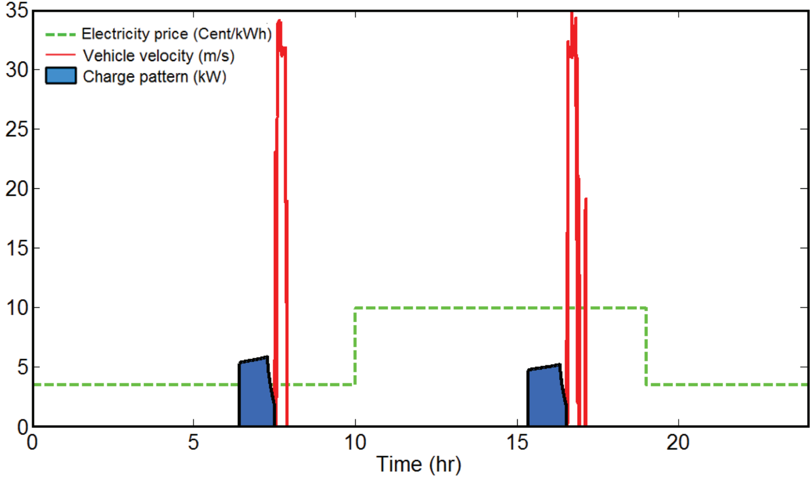


Open Questions: Modeling, state estimation, control/optimization, implementation

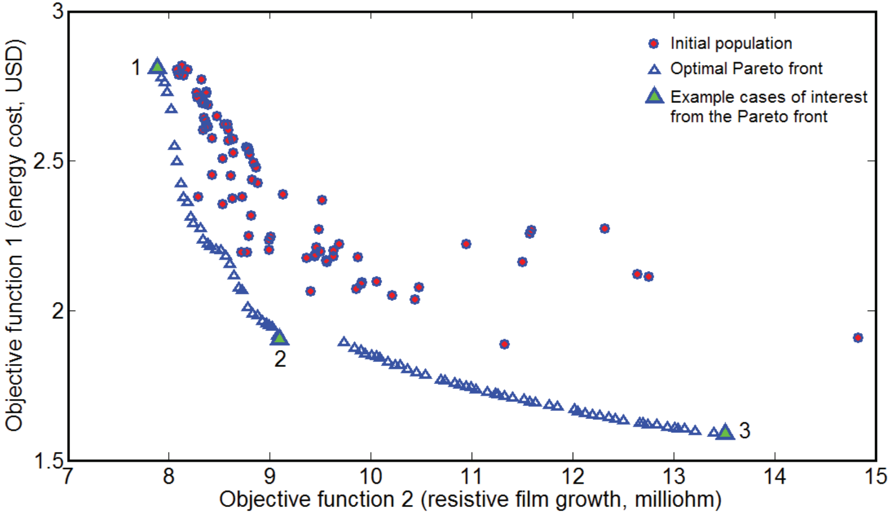
When to charge PEVs?

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?



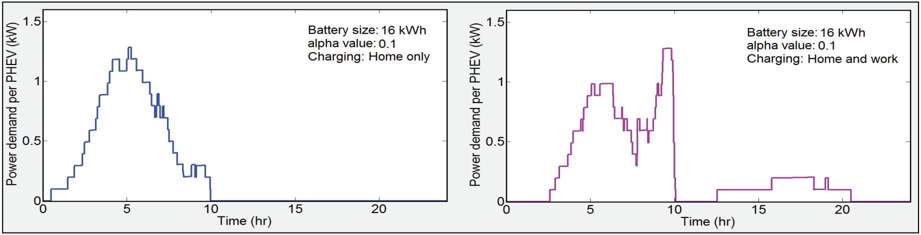
Multiobjective Optimization

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



Outline

Summary of TCL Modeling & Estimation

1. Modeling
   - Aggregate dynamics via PDEs
   - Homogeneous vs. Heterogeneous
2. Estimation
   - State observer via PDE backstepping
   - Parameter identification algorithms
3. UCSD Campus Deployment
4. PEV-Grid Integration
   - Extension of aggregation approach

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Xie Xie!

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