Buildings & Cars as Power Plants?

Aggregating Flexible Loads in the Smart Grid

Scott Moura

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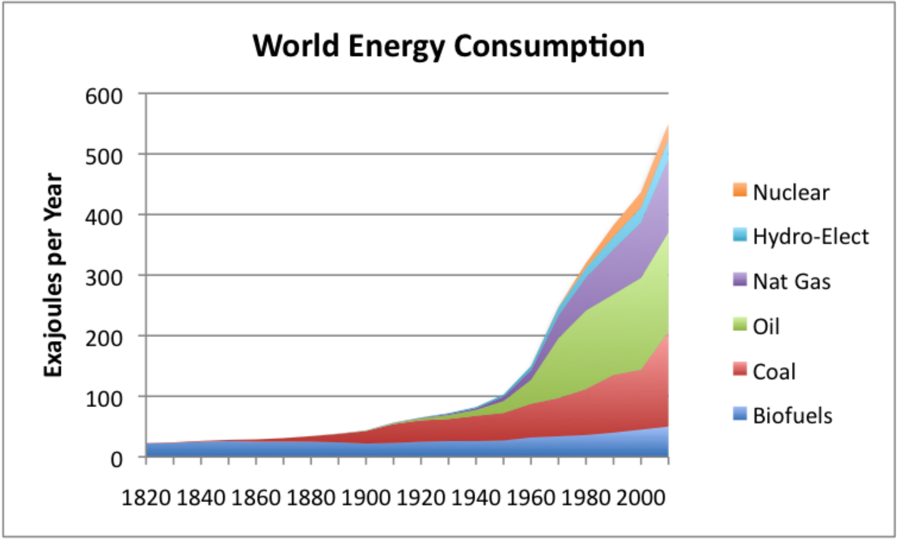
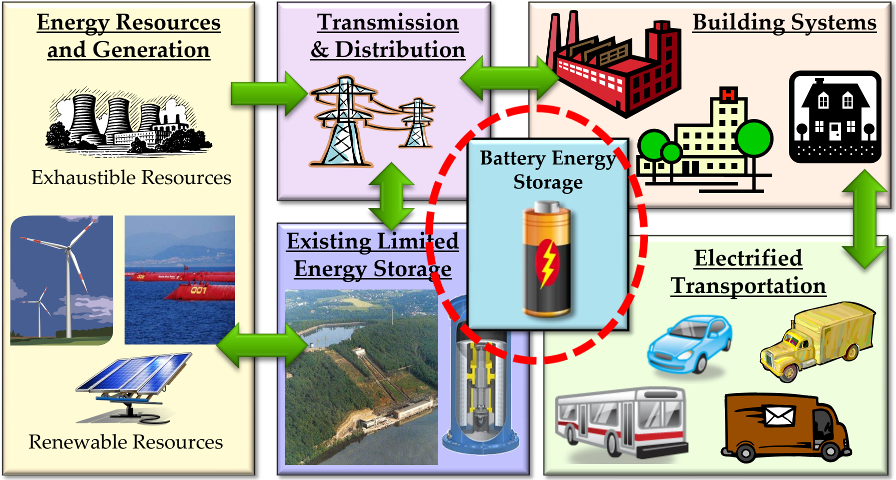
Cymer Seminar



Source: Vaclav Smil Estimates from Energy Transitions

Vision for Future Energy Infrastructure



Energy Systems of Interest

Buildings	Transportation
(e.g., HVAC, EWH)	(e.g., PEVs)

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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 Demand Response Problem

Needs:

(1) Integrate renewables, (2) enhance power system resilience & economics

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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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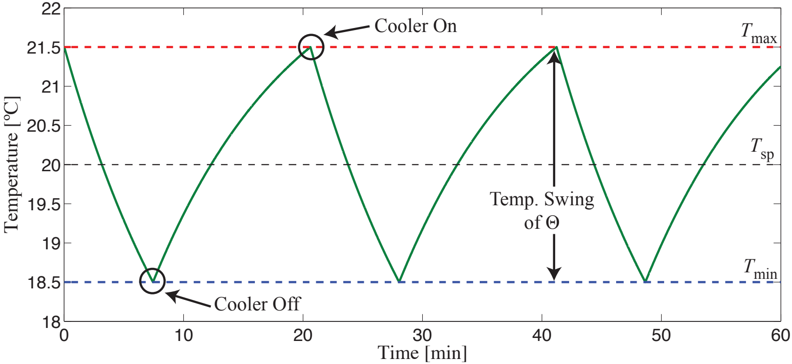
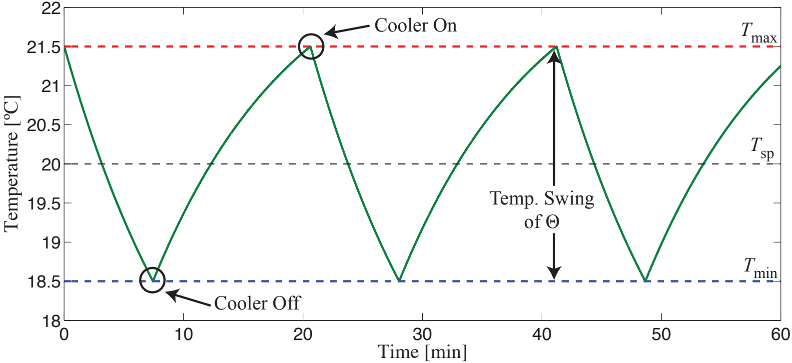
The Punchline

Exploit flexibility of TCLs for power system services

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 / $^\circ$C, in COOL state, @ temp T, time t
$v(T,t)$	# TCLs / $^\circ$C, in HEAT state, @ temp T, time t

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

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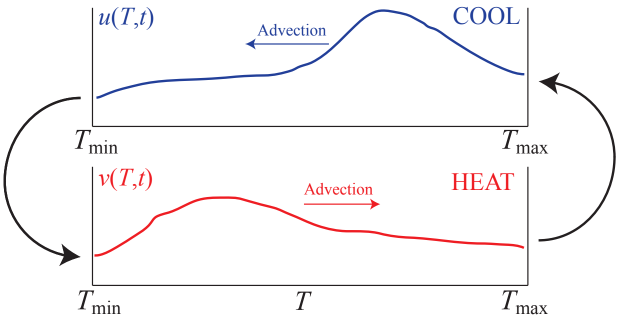
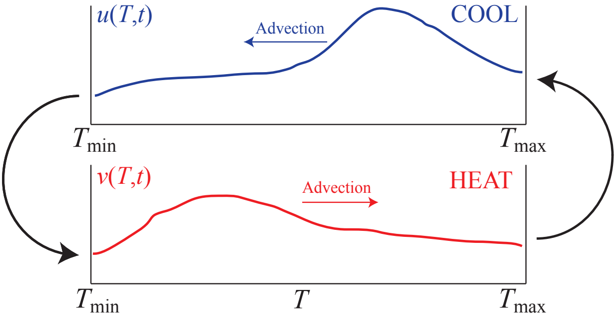
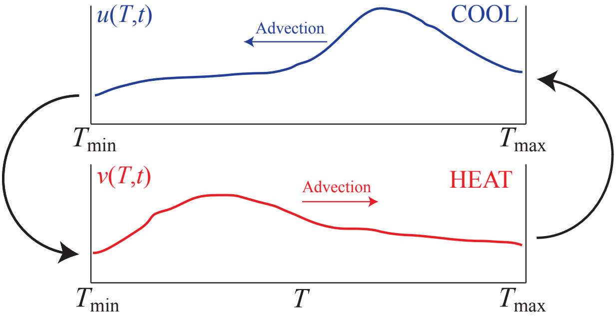


PDE Model of Aggregated TCLs



Video of 1,000 TCLs

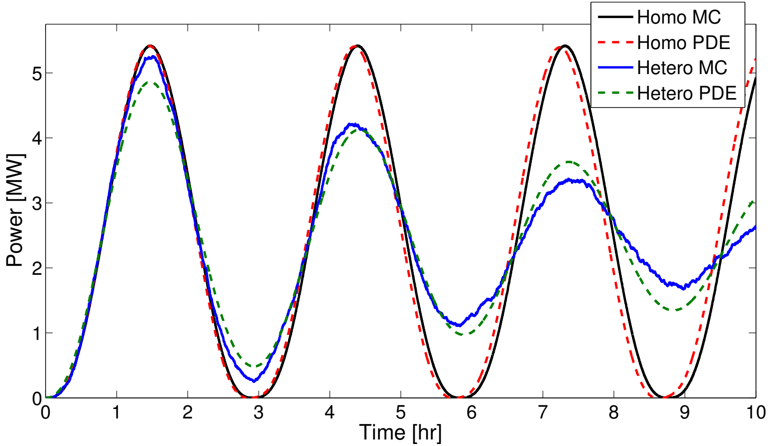
PDE Model of Aggregated TCLs



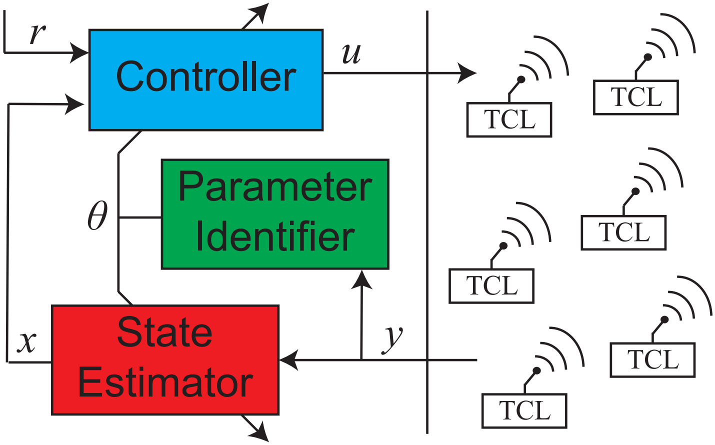
$$u_t(T,t) = \alpha\lambda(T)u_T(T,t) + \alpha u(T,t)$$
$$v_t(T,t) = -\alpha\mu(T)v_T(T,t) + \alpha v(T,t)$$
$$u(T_{\max},t) = q_1 v(T_{\max},t)$$
$$v(T_{\min},t) = q_2 u(T_{\min},t)$$

Video of 1,000 TCLs

Model Comparison



Feedback Control System



PDE State Estimator

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

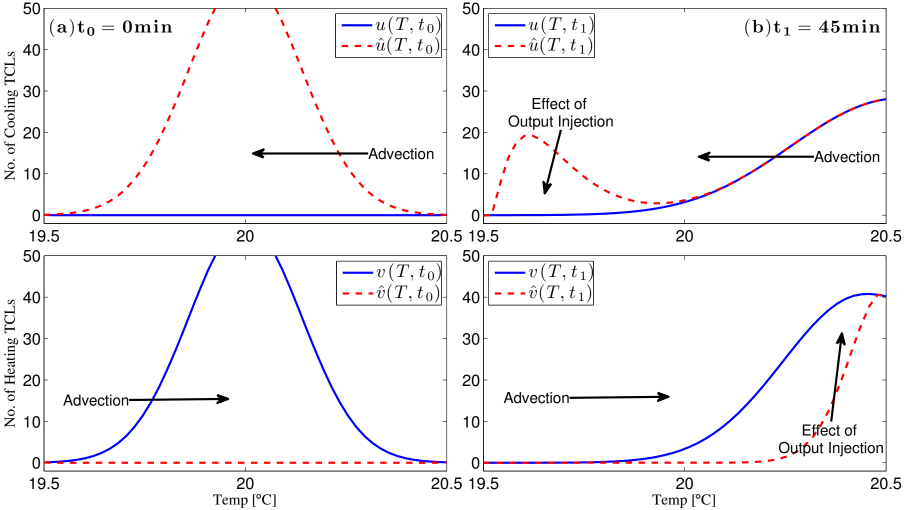
$$\begin{aligned}
\tilde{u}_t(x,t) &= \alpha\lambda(x)\tilde{u}_x + \alpha\tilde{u} + \beta\tilde{u}_{xx} - p_1(x)\tilde{u}(0,t) \\
\tilde{u}_x(0,t) &= -p_{10}\tilde{u}(0,t) \\
\tilde{u}(1,t) &= 0 \\
\\
\tilde{v}_t(x,t) &= -\alpha\mu(x)\tilde{v}_x + \alpha\tilde{v} + \beta\tilde{v}_{xx} - p_2(x)\tilde{v}(1,t) \\
\tilde{v}(0,t) &= 0 \\
\tilde{v}_x(1,t) &= -p_{20}\tilde{v}(1,t)
\end{aligned}$$

Goal: Design estimation gains:

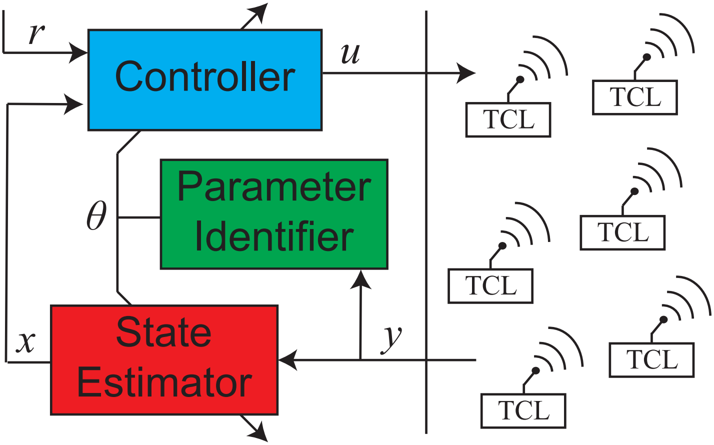
- $p_1(x), p_2(x) : (0,1) \to \mathbb{R}$
- $p_{10}, p_{20} \in \mathbb{R}$

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

Simulations



Feedback Control System



Parameter Identification

Uncertain parameters

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

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

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

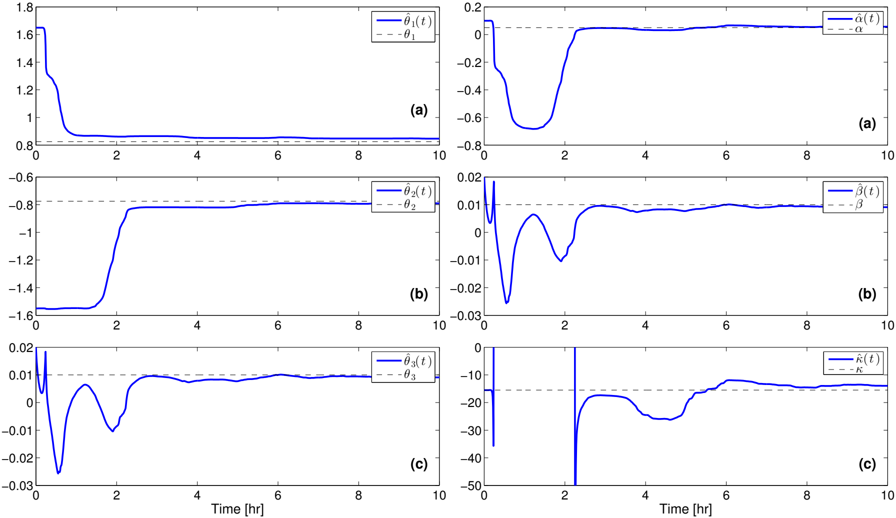
$$P(t) = \frac{\overline{P}}{\eta} \int_0^1 u(x,t) dx$$

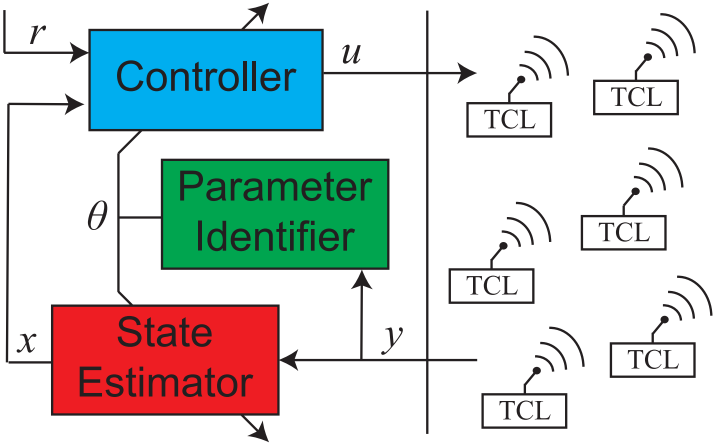
Assumptions:

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

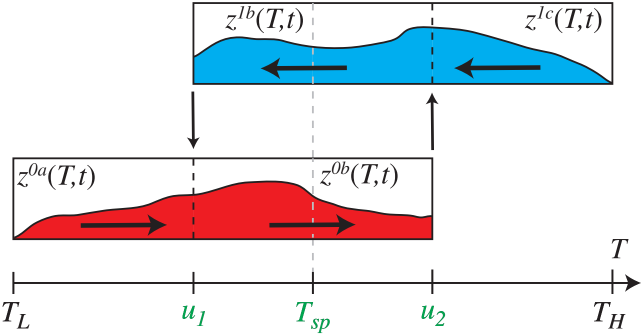
Simulations

Identified from Population of 1,000 Heterogeneous TCLs




r
Controller
u
θ
Parameter Identifier
x
State Estimator
y
TCL
TCL
TCL
TCL
TCL
TCL

Set-point / Deadband Control

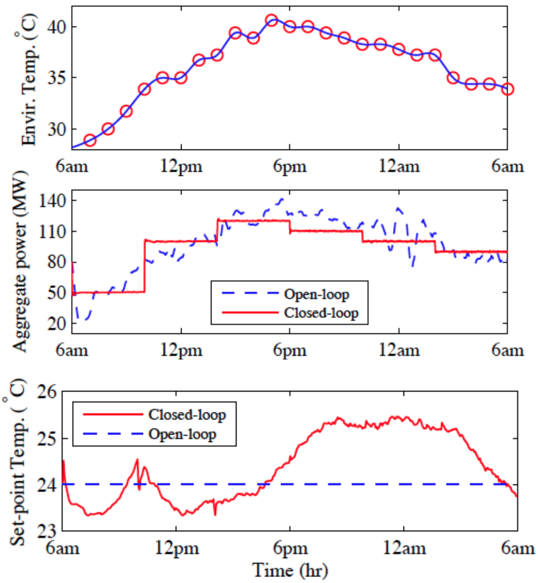


$$
\begin{aligned}
z_t^{1j}(T,t) &= \alpha\lambda(T) z_T^{1j}(T,t) + \alpha z^{1j}(T,t), \qquad j \in \{b,c\} \\
z_t^{0j}(T,t) &= -\alpha\mu(T) z_T^{0j}(T,t) + \alpha z^{0j}(T,t), \qquad j \in \{a,b\}
\end{aligned}
$$

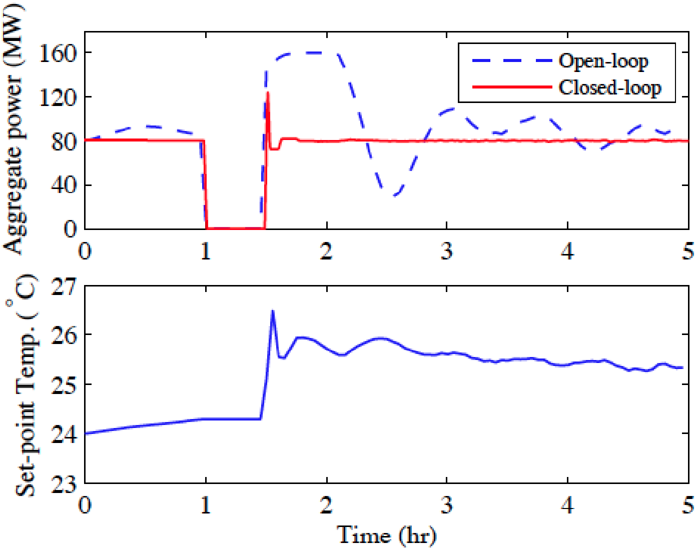
with boundary conditions

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

Aggregate Power Control



Aggregate Power Control



UC San Diego Campus: A Living Laboratory

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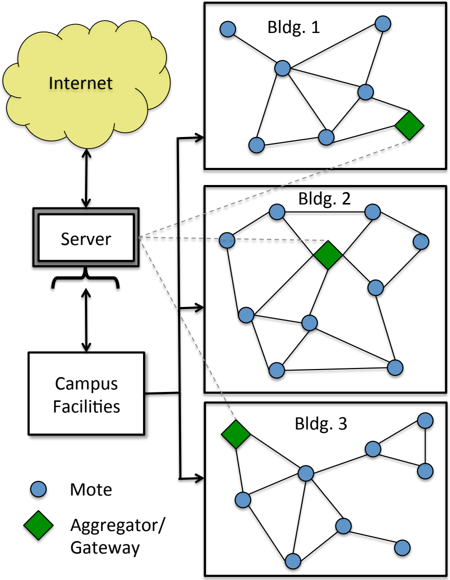
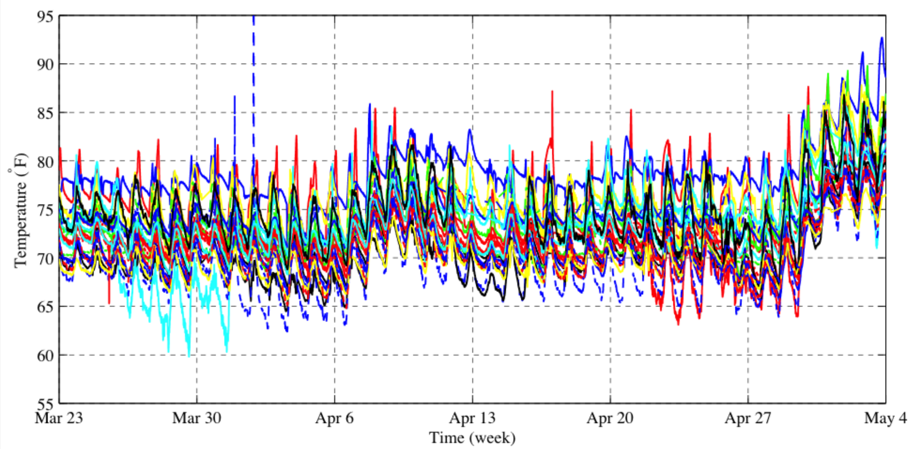
Goal: DR for Bldg Energy Mgmt

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

Sensor Nodes (Temp & Humidity)



UCSD Office Temperature Data



Temperature variation of monitored spaces over six week. The peak point of room temperature happens at midnight.

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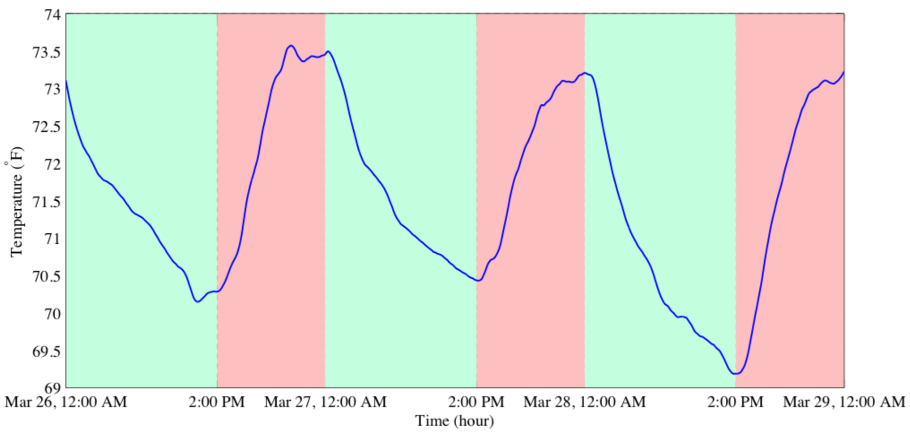
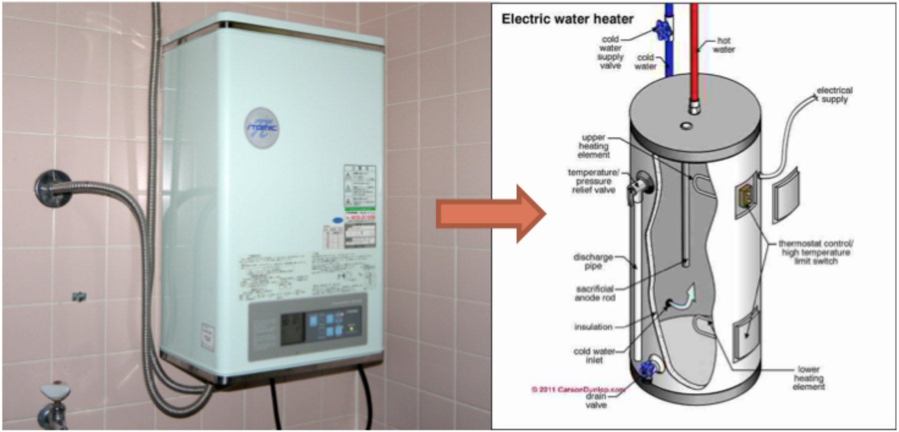


The HVAC system works in a time scheduled manner. The green parts indicate off regions and the red bands show on regions.

Aggregating Electric Water Heaters (EWH) | EDF



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(e.g., HVAC, EWH)	(e.g., PEVs)

The Vehicle-Grid Integration (VGI) Problem

Needs: Resilient and sustainable energy/transportation infrastructure

Obstacle: Unprecedented constraints and demands on grid

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

Government Initiatives

Vehicle-Grid Integration Roadmap

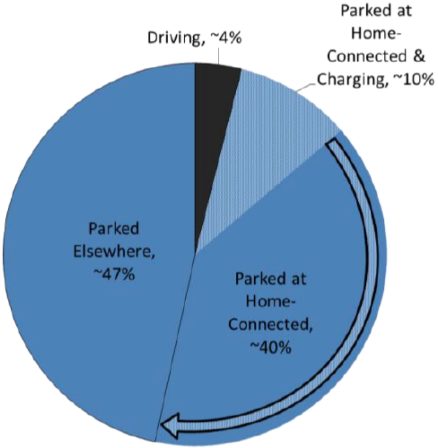
– 1.5M ZEVs in California by 2025

"Vehicle electrification and smart grid technology implementation present an opportunity for EVs, through charging strategies and aggregation, to support and provide valuable services to contribute to reliable management of the electricity grid"

DOE Congressional Budget Request

"The lack of understanding of the impact that the large-scale market penetration of PEVs may have on the electric grid (such as charging during on-peak hours, coordination of charging events, and time-of-day pricing) represents a challenge that must be overcome in order to achieve market success. "

PEV Energy Storage: How much, when, and where?



Estimated percent of time PEVs spend by location and activity.

A. Langton and N. Crisostomo, “Vehicle-grid integration: A vision for zero-emission transportation interconnected throughout Californias electricity system,” California Public Utilities Commission, Tech. Rep. R. 13-11-XXX, 2013.

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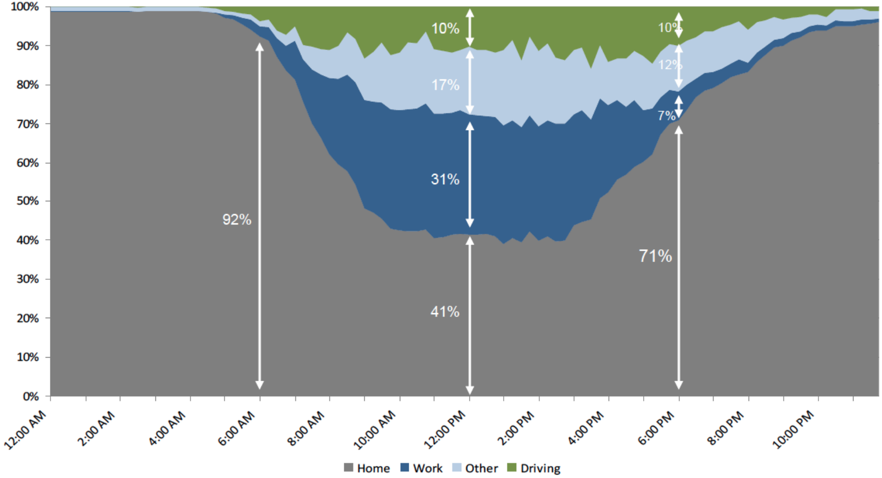

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Project-based Course on V2G System

- Fleet of eScooters
- Collect shared mobility data, design VGI system
- Learn hardware, software, algorithms, big data, cloud-based computing
- Berkeley Energy and Climate Lectures Curriculum Innovation Award

Google
App Engine

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

Cloud Enabled Smart Charging of PEVs

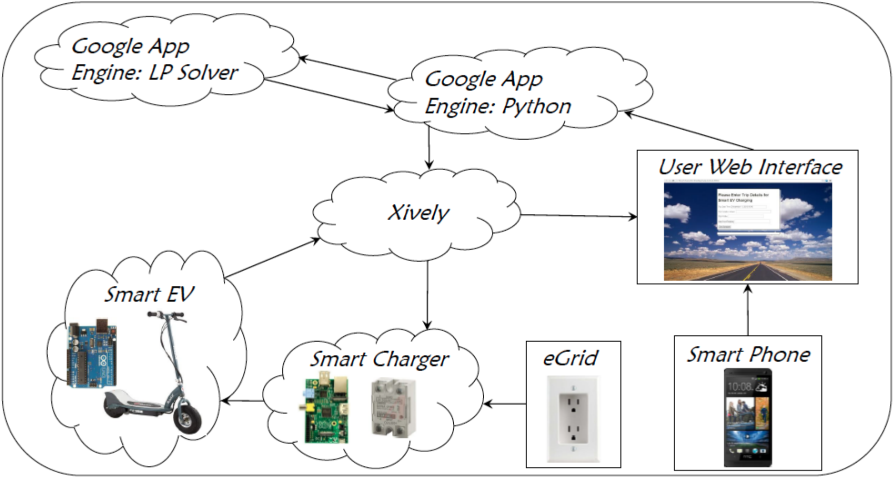


Figure 2. On the Cloud Optimization System for Smart EV Charging

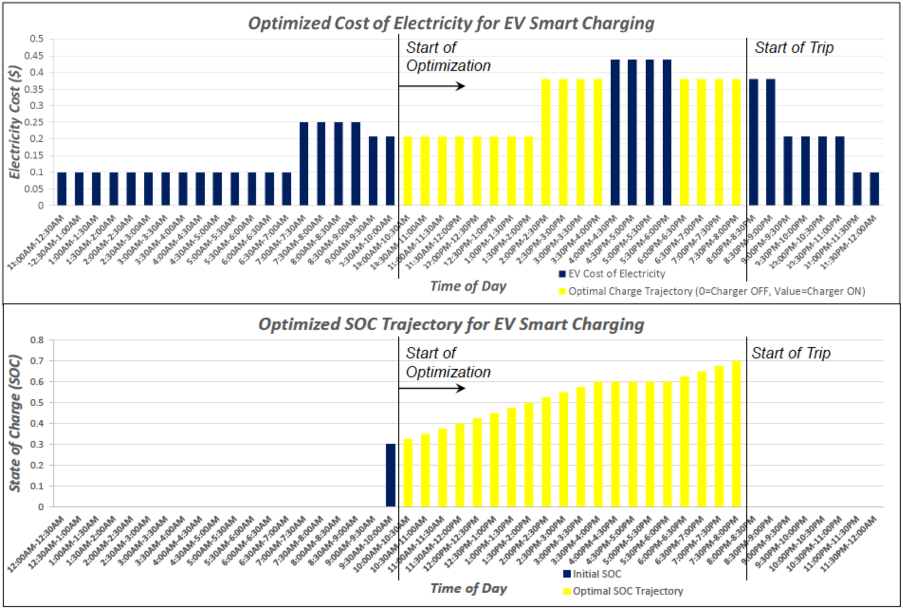
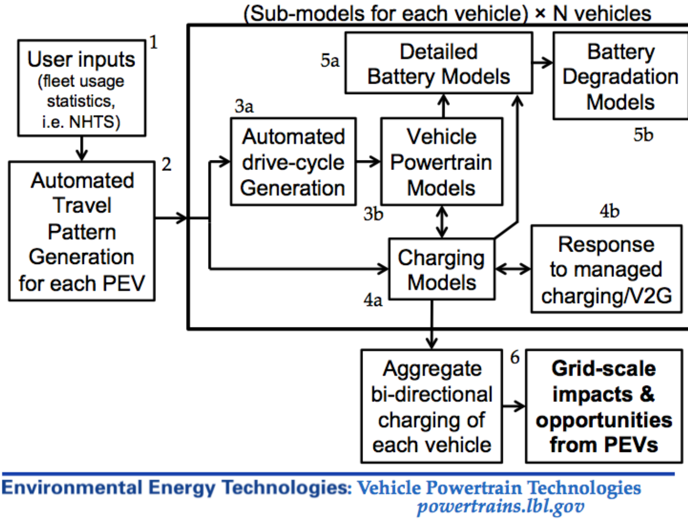


Figure 3. Optimal Charge Cost and SOC Trajectory

V2G-Sim (Lawrence Berkeley National Lab)

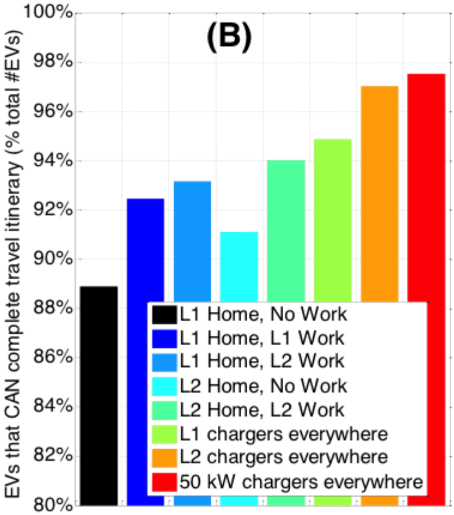
A simulation platform for model-based design and analysis of vehicle-grid integration

A simulation platform for model-based design and analysis of vehicle-grid integration

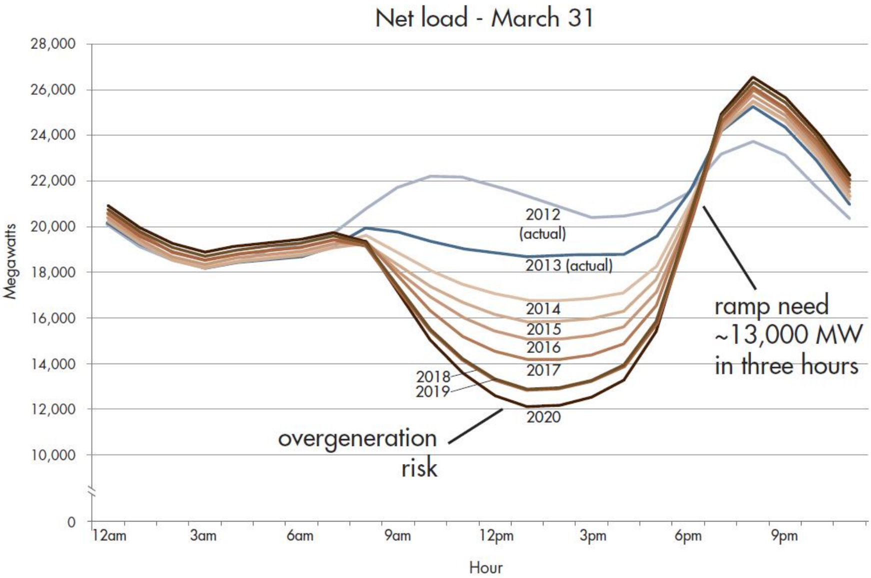


V2G-Sim (Lawrence Berkeley National Lab)

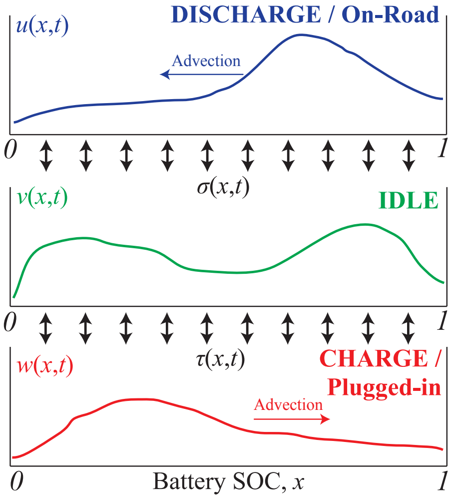
Do we need fast charging, or are standard home outlets enough?



The duck curve shows steep ramping needs and overgeneration risk

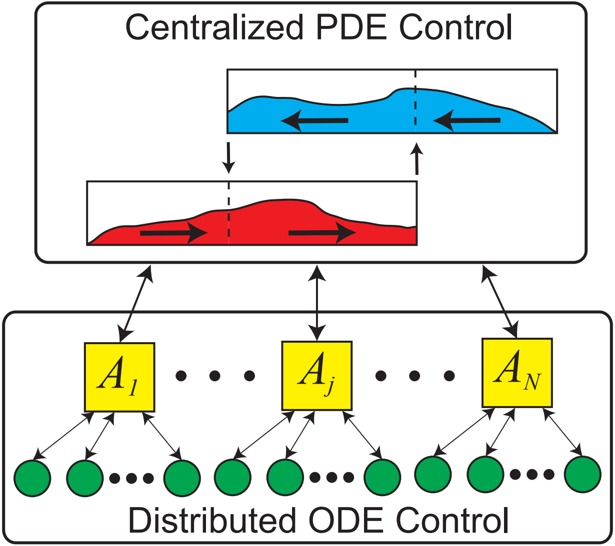


Modeling Aggregated PEVs w/ PDEs

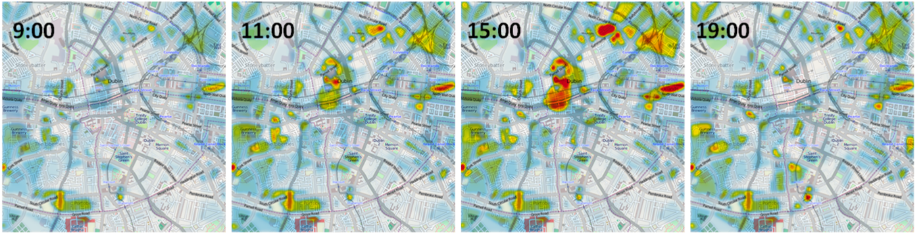


$u(x,t)$	# PEVs / SOC, in DISCHARGE state, @ SOC x, time t
$v(x,t)$	# PEVs / SOC, in IDLE state, @ SOC x, time t
$w(x,t)$	# PEVs / SOC, in CHARGE state, @ SOC x, time t

Hierarchical Control

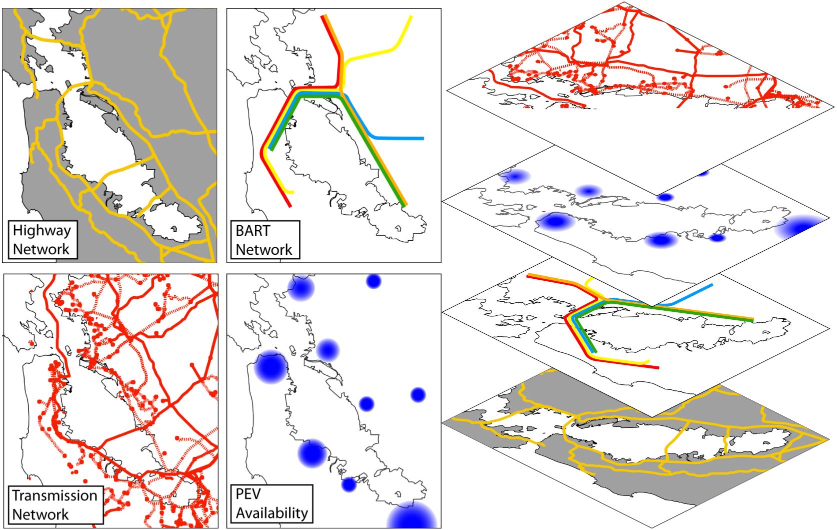


Spatio-Temporal Evolution



Population densities estimated from cell phone usage at different time of the day: morning (left), shopping time (both images in the centre), evening (right) (Source: Kaiser and Pozdnoukhov 2013)

Coupled Transportation-Energy Networks



QUESTIONS?

Energy, Controls, and Applications Lab (eCAL)

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Control & Optimization w/ Application to Energy Systems

Sample Course Projects:

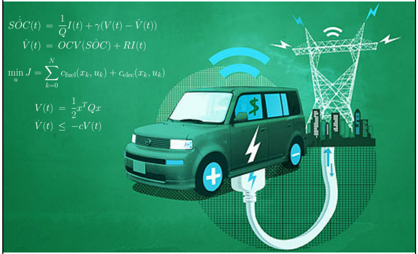
- Aggregate Modeling & Control of PEV Fleets
- Optimal Charging & Vending of Shared eBike Fleets
- Smart Home Thermostat
- Optimal Energy Storage Placement in CA
- Smart Home Energy Management w/ Solar
- Battery Estimation
- Building Lighting Controls
- Rooftop & Centralized Solar Generation in Nicaragua

CE 290:002

Energy Systems & Control

Spring 2014: MWF 10-11

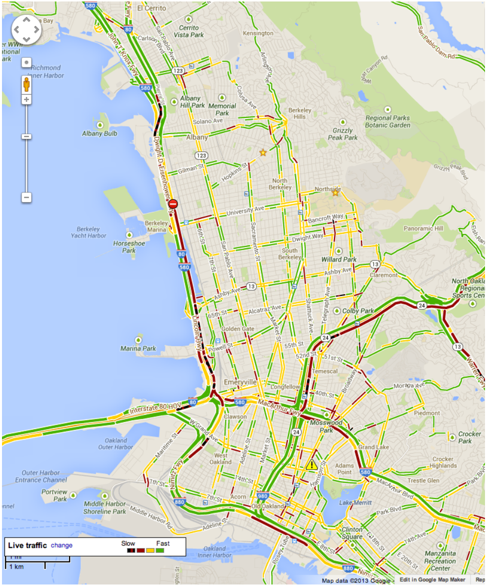
Prof. Scott Moura



Topics Include:

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

Optimize PHEV Energy Management w/ Real-time Traffic Data



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Why Care?

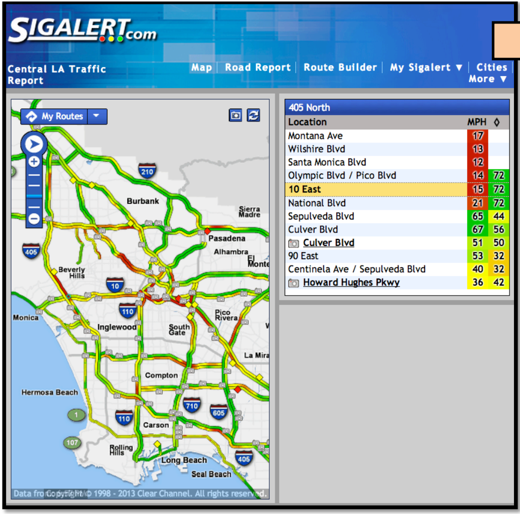
The Problem

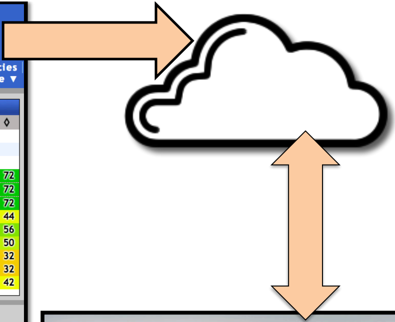
- 54.5 MPG CAFE by 2025
- Increased CAFE $\rightarrow$ Increased powertrain tech costs
- Urbanization $\rightarrow$ traffic $\rightarrow$ lower MPG

An Interesting Solution

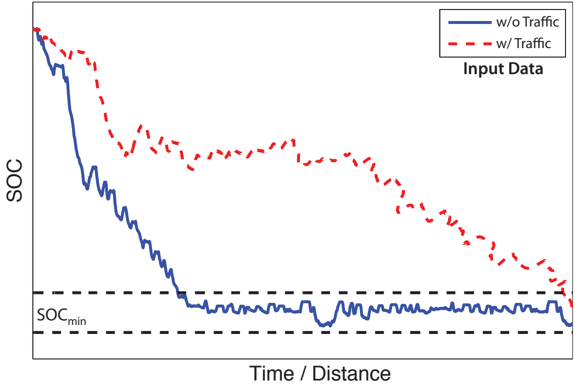
- Real-time traffic data (Google Traffic, PEMS, SigAlert.com) is available
- Cloud computing enables data retrival, optimization, communication
- Adapt PHEV energy management to real-time traffic conditions

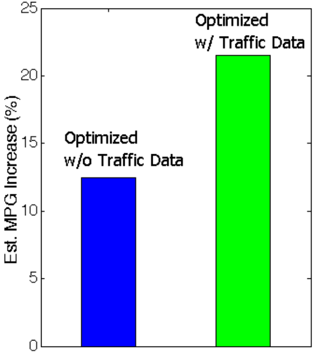
Optimize PHEV Energy Management w/ Real-time Traffic Data





Traffic Data





- Maximize MPG by blending engine & battery such that min battery charge (SOC) is reached exactly at end of trip
- All trips are different
- Real-time traffic data provides speeds, elevation, accidents, etc.