

# Data, Controls, and Optimization: Studies in Building Energy Management

Scott Moura

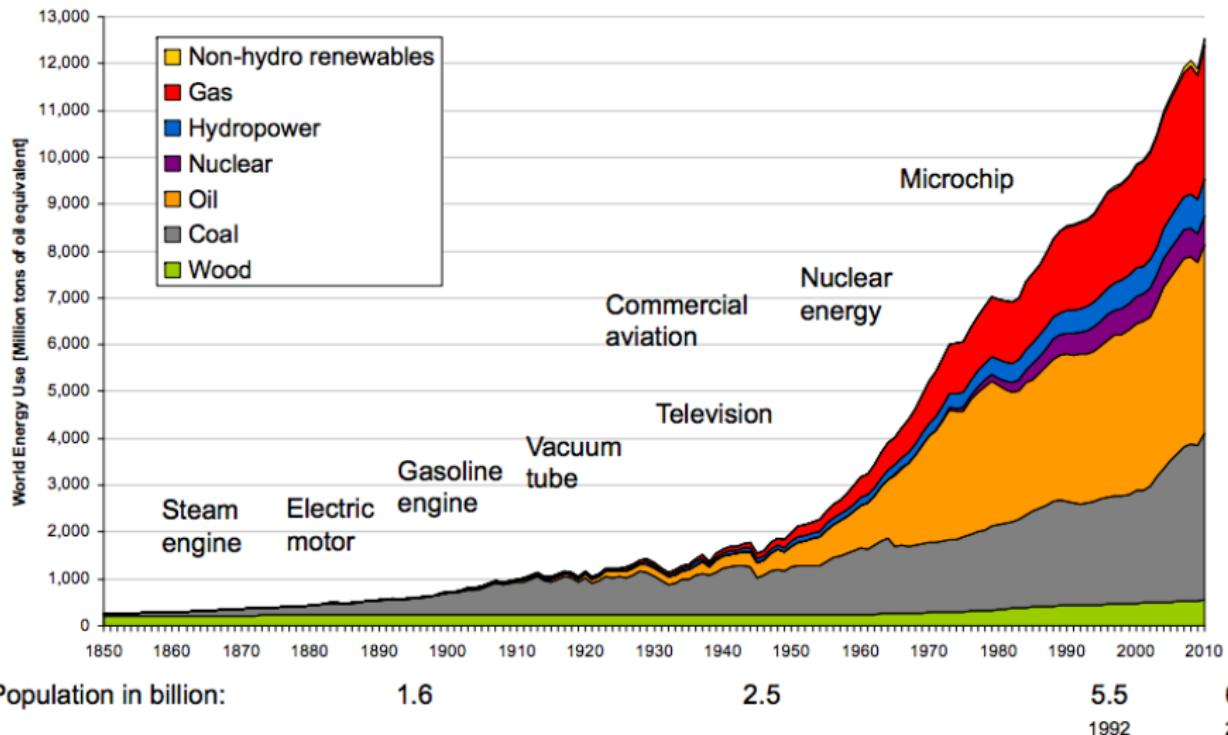
Assistant Professor | eCAL Director  
Civil & Environmental Engineering  
University of California, Berkeley

Center for the Built Environment | Brown Bag Lunch



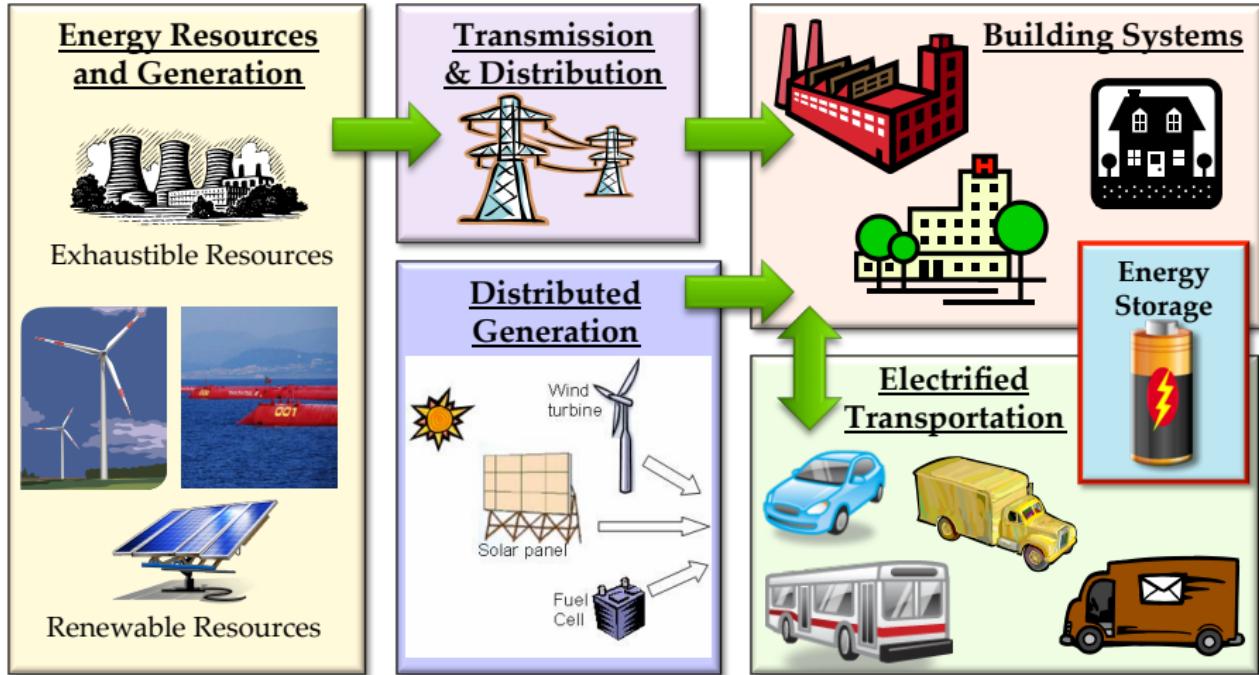
# Contributors to this Talk...

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<b>Visiting Ph.D.</b>	Chao Sun [Beijing Inst. of Tech.]
<b>Visiting Scholar</b>	Xiaohua Wu [Xihua University]
<b>Colleagues</b>	Fengchun Sun [Beijing Inst. Tech.], Jae Wan Park [UC Davis]

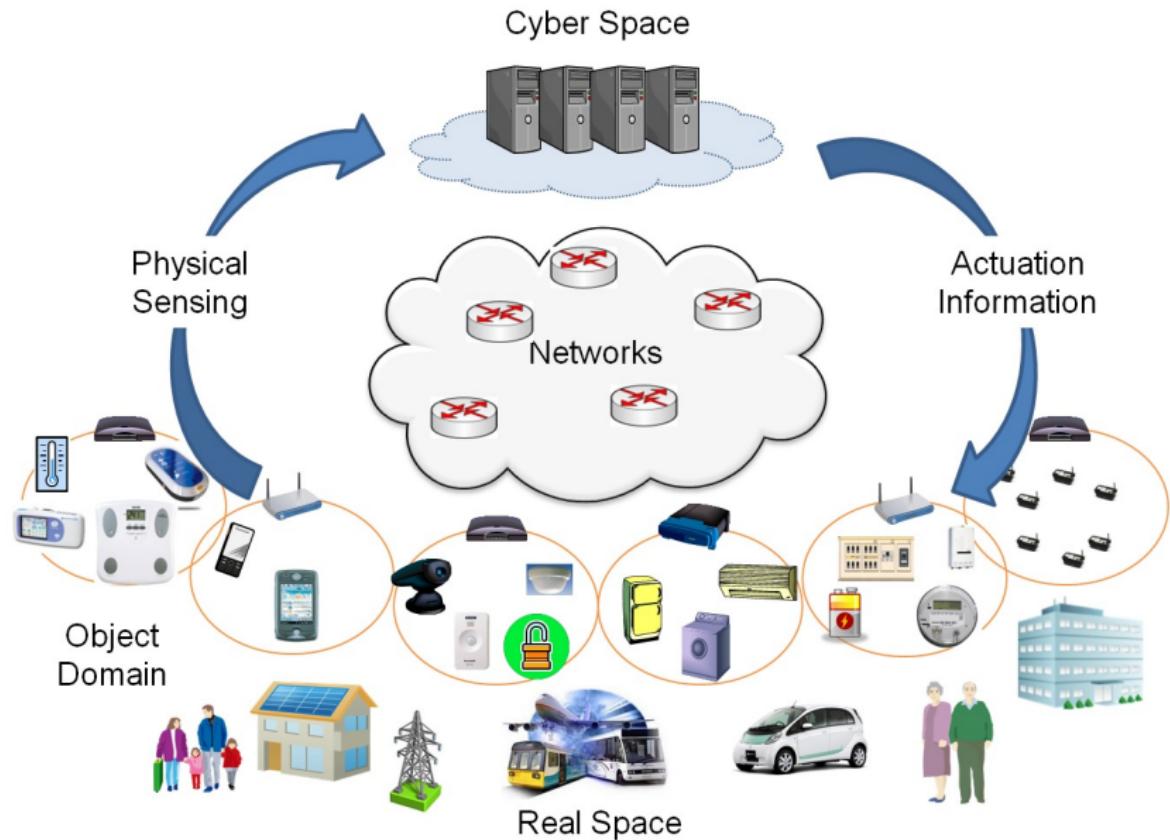


Compiled from data by Gruebler (1999), BP Statistical Review (2011) Nakicenovic & Gruebler (2000)

# Vision for Future Energy Infrastructure



# Cyber Physical Systems



# Outline

- 1 Forecasting Building Electric Demand
- 2 Residential Buildings with Solar & Storage
- 3 Integrating PEV Energy Storage with Buildings
- 4 Open Thoughts & Shameless Advertisements

# The Electricity Demand Forecasting Problem

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## Some Motivating Facts

Emit	48% of carbon emissions
Consume	39% of total energy 71% of electricity 54% of natural gas
Netflix Prize	1M USD Award for Best Algorithm Predict Subscriber Movie Ratings (1 to 5 stars) Competing algorithms converged on similar concepts

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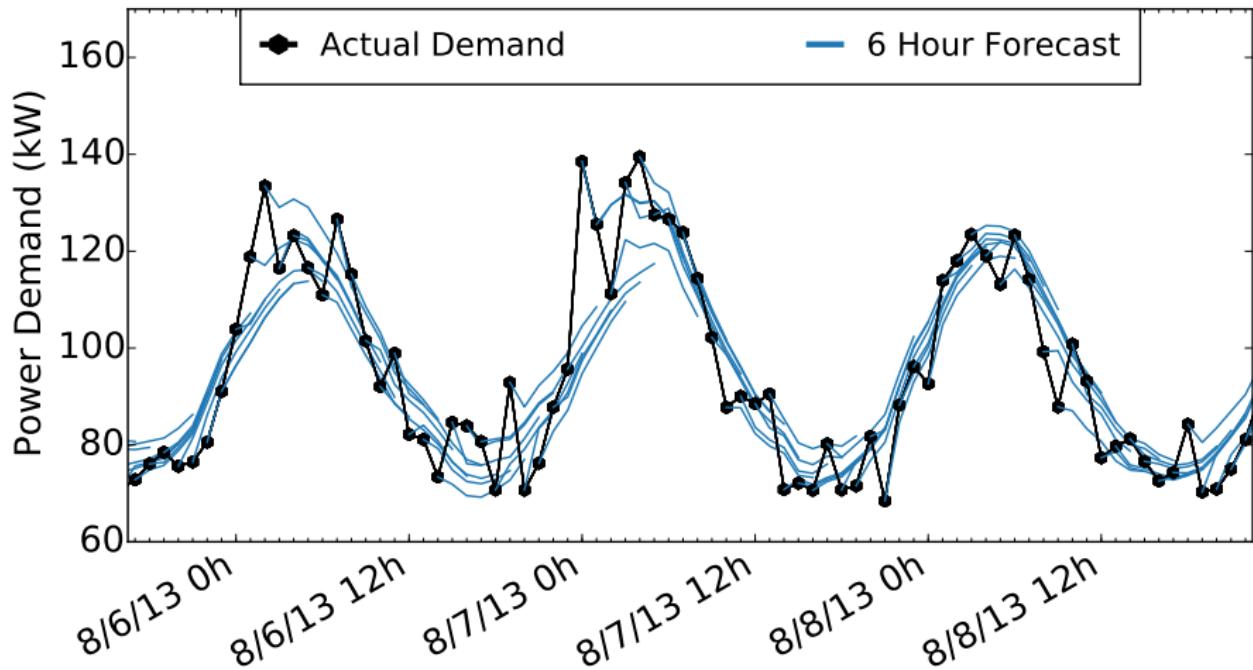
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## Punchline

Apply lessons from open competition to building electricity forecasting

# Electricity Demand Forecasting



# Stacked Ensemble Learning

inspired by Netflix prize

Suppose you have already constructed  $M$  forecasting models, with prediction output  $\hat{y}_s \in \mathbb{R}^m$ ,  $s = 1, \dots, M$ .

Consider a weighted sum of these models

$$\hat{y}_{\Sigma} = \sum_{s=1}^M \theta_s \hat{y}_s$$

with  $\theta_s \in \mathbb{R}$  the weighting coefficient of sub-model  $s$ , for  $s = 1, \dots, M$ .

# Regression

Employ Least Squares with  $L_2$  regularization (a.k.a. “Ridge” regression for scikit-learn users) to learn weights  $\theta_s$  for  $s = 1, \dots, M$

$$\min_{\theta} \sum_{i=1}^N \left( y_i - \sum_{s=1}^M \theta_s \hat{y}_{s,i} \right)^2 + \lambda \sum_{s=1}^M \theta_s^2$$

$\theta_s \in \mathbb{R}$  : weights for sub-model  $s$ ,  $\theta = [\theta_s]_{s=1, \dots, M}$

$y_i \in \mathbb{R}^m$  :  $i^{th}$  observed electricity demand

$\hat{y}_{s,i} \in \mathbb{R}^m$  :  $i^{th}$  predicted electricity demand for sub-model  $s$

$i = 1, \dots, N$  : where  $N$  is the number of data samples

$\lambda$  : Weight for regularization penalty

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Consider fitting a model of Wurster on July 15 and September 15.  
Will the results be different?

# Online/Real-time Regression

Answer: YES! Building behavior evolves over time! So should the models!

Compute time-varying weights using a retrospective moving horizon optimization

$$\min_{\theta_t} \sum_{i=1}^T \left( y_{t-i} - \sum_{s=1}^M \theta_{t,s} \hat{y}_{s,t-i} \right)^2 + \lambda \sum_{s=1}^M \theta_{t,s}^2$$

$\theta_{t,s} \in \mathbb{R}$  : weights at time-step  $t$ , for sub-model  $s$ ,  $\theta_t = [\theta_{t,s}]_{s=1, \dots, M}$

$y_{t-i} \in \mathbb{R}^m$  : observed electricity demand at time step  $t - i$

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$i = 1, \dots, T$  : where  $T$  is the length of the retrospective time horizon

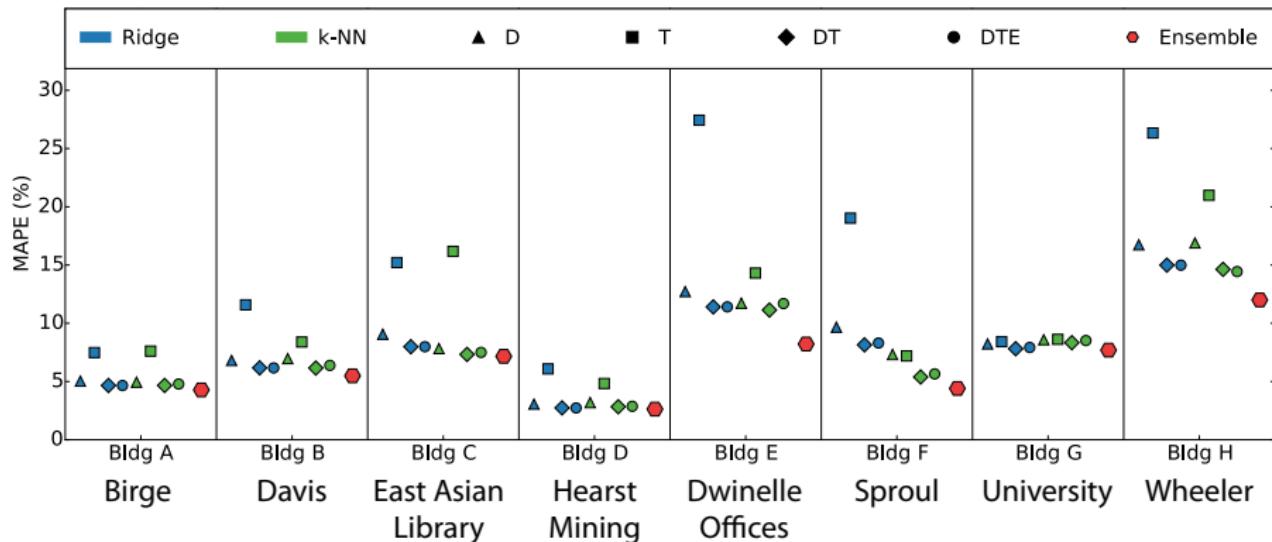
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# Electricity Demand Forecasting

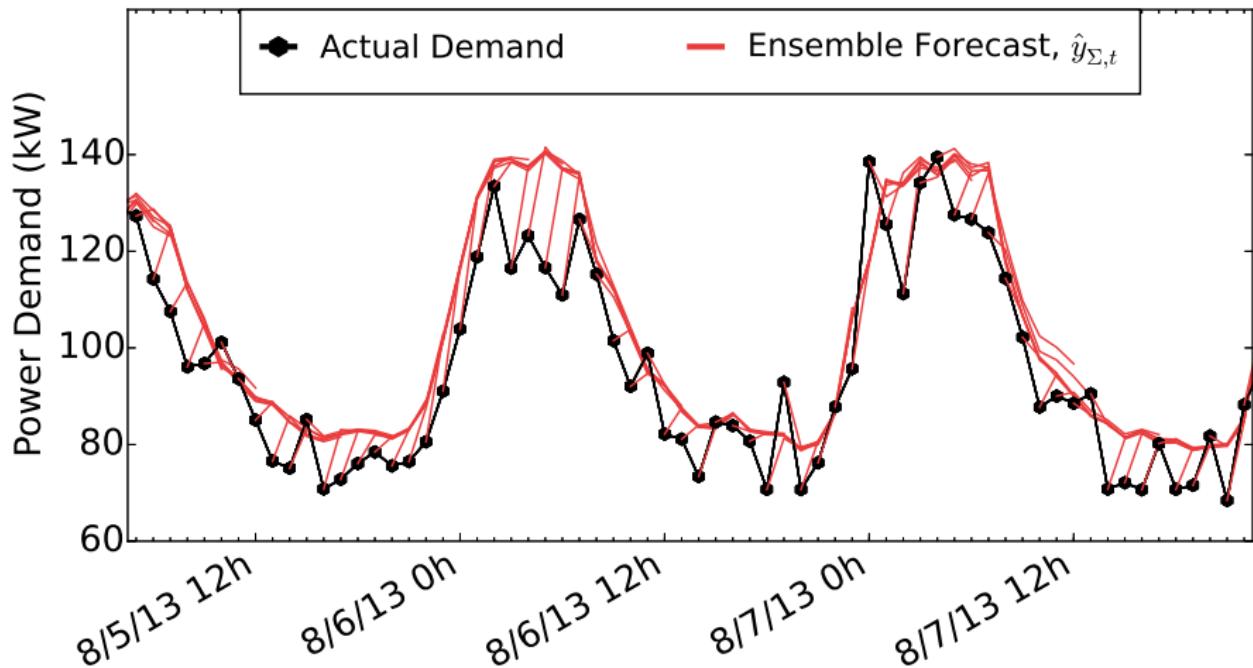
**Train (offline):** 8 buildings w/ 8 models each; data from 1/2013 to 6/2014

**Test (online):** Generate 6 hour forecasts; data from 7/2014 to 12/2014

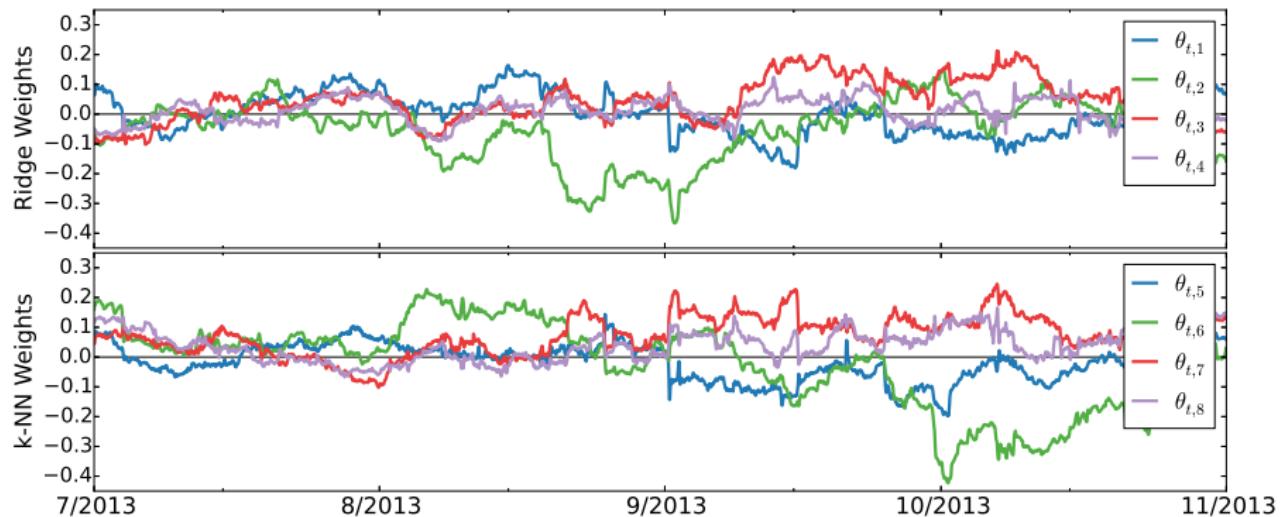
$$MAPE = 100\% \cdot \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_{i,\Sigma}}{y_i} \right|$$



# Electricity Demand Forecasting | Dwinelle Offices



# Electricity Demand Forecasting | Time-Varying $\theta_{t,s}$



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# Solar+Storage - An Emergent Market



# The Building Solar+Storage Problem

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## Some Motivating Facts

Policy	50% renewables in CA by 2030, 100% in Hawaii by 2045
Climate	2011 Tsunami in Japan → energy security and reliability
Costs	Li-ion battery pack costs decreasing toward 350 USD/kWh
Data	Over 50M (43%) of US homes have smart meters
Hybrid Vehicles	Photovoltaics/Grid ↔ Engine Home Demand ↔ Driver Power Demand Battery Storage ↔ Battery Storage

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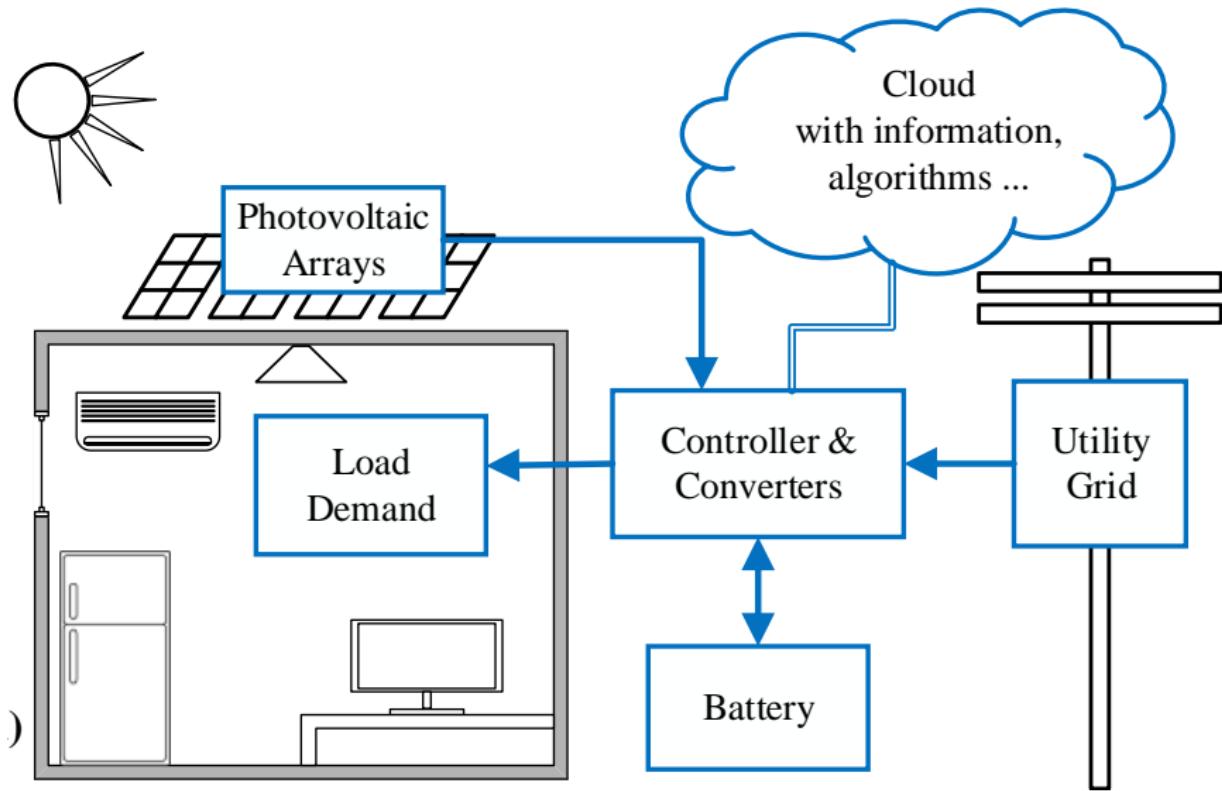
Apply & Extend ~10 years of HEV Energy Management  
Control Research to Building Solar+Storage

## Features of Published Energy Management Frameworks for Buildings

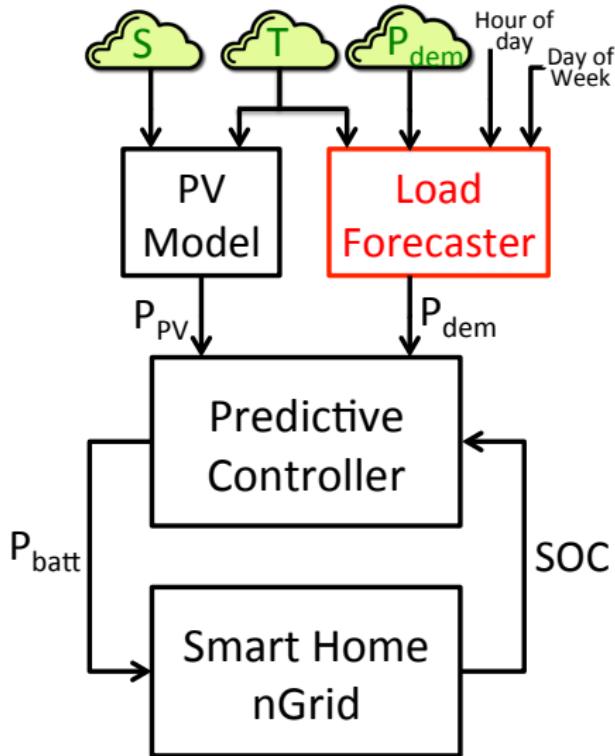
<b>Features</b>	[1]	[2]	[3]	[4]	[5]	[6]	[7]	Our Paper
Problem Formulation	Lin	Lin?	Lin	NL?	Lin	Lin	thermal circuit	NL
Solver	LP	DP	MILP	GA	MILP	MILP	LP?	DP
Battery Model	Lin	Lin (Int)	Lin	Lin (Int)	Lin (Int)	Lin (Int)	Lin (Int)	NL
Model Predictive Control							Y	Y
Load Forecast	Gauss Noise	Known	Known	Known	Known	Known		Y (ANN)
Sensitivity on Load Forecast Error			Y? Gauss					Y
PV Generation Forecast	Gauss Noise	Known		Y (ANN)		Known		Y (API)
Carbon Emission Reduction								Y WattTime
Battery Aging		Y				Y		Y

Blank = feature not used or not mentioned

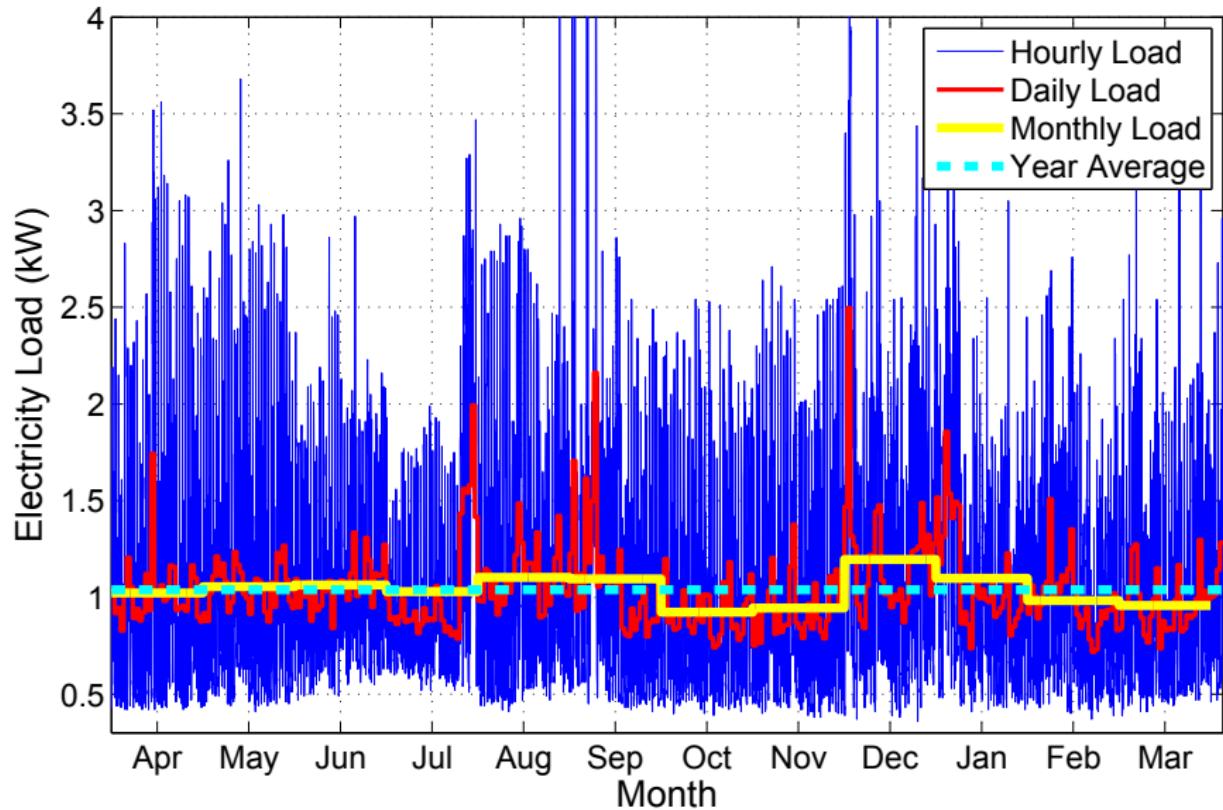
# Residential Buildings with Solar & Storage



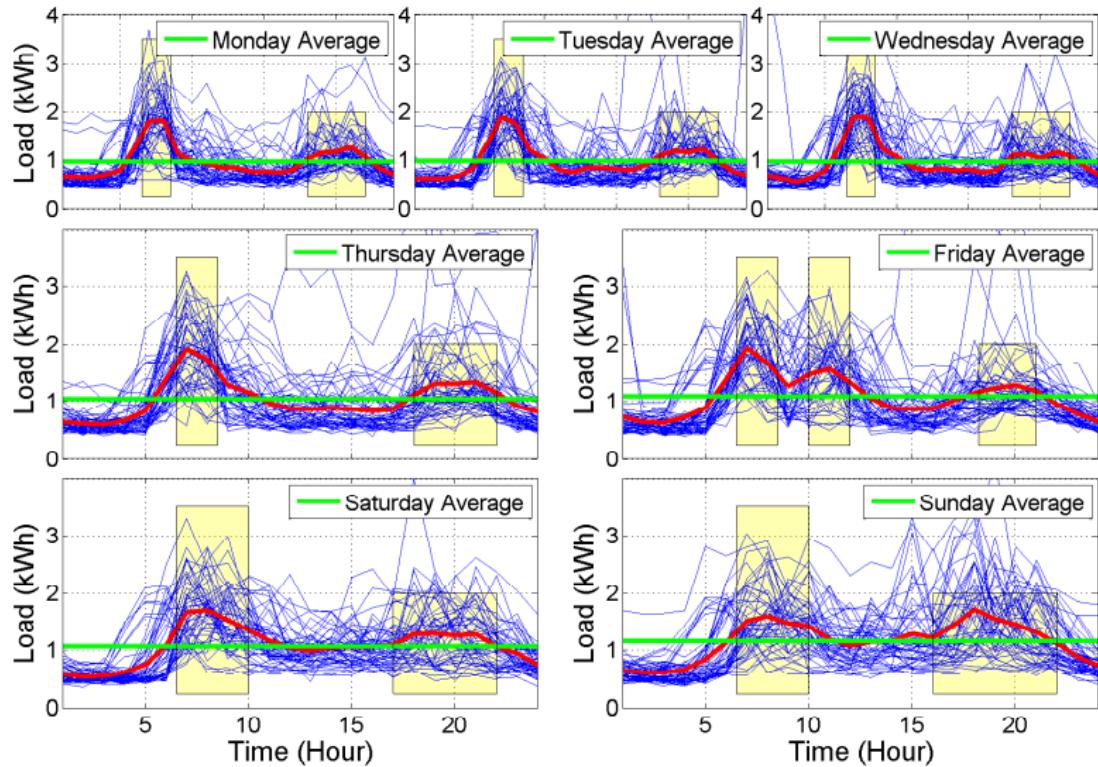
# Predictive Controller with Load/Weather Forecasting



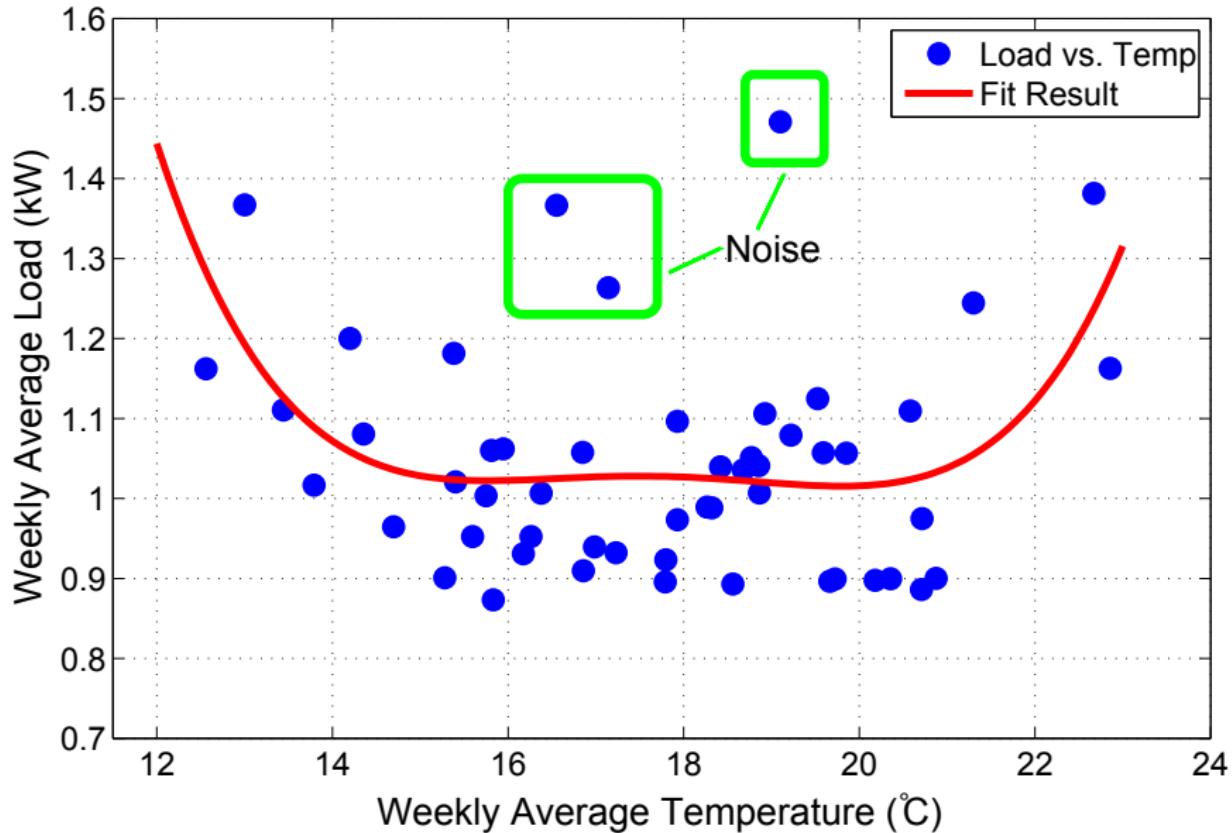
# Single-Family Home Energy Patterns in LA



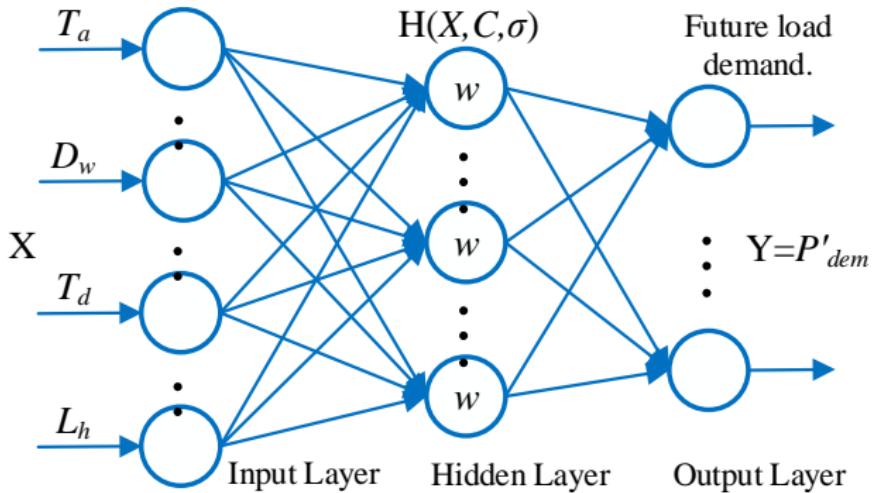
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# Single-Family Home Energy Patterns in LA



# Artificial Neural Network (ANN)

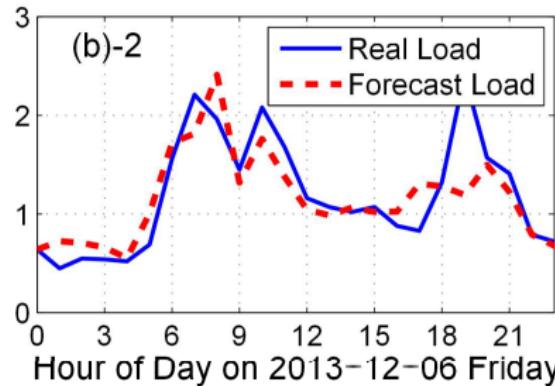
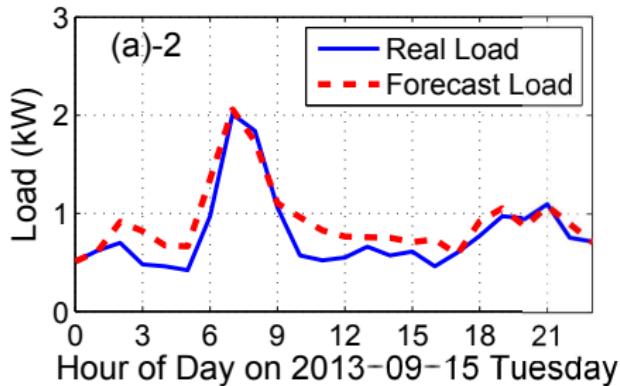
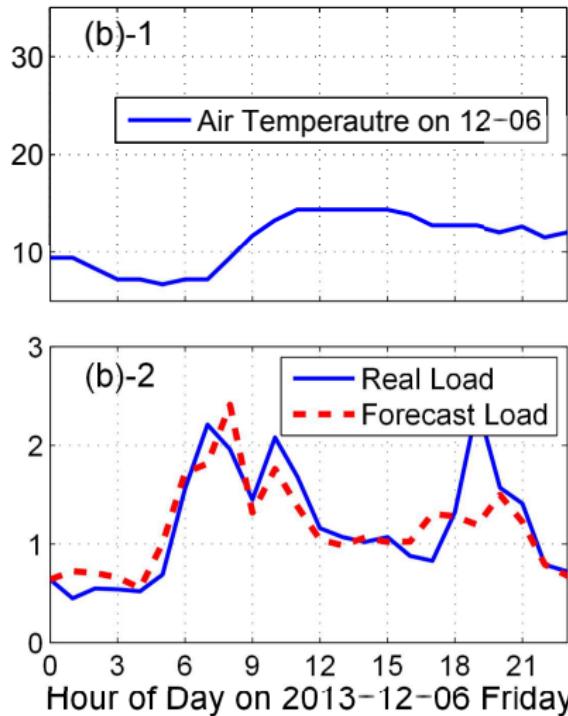
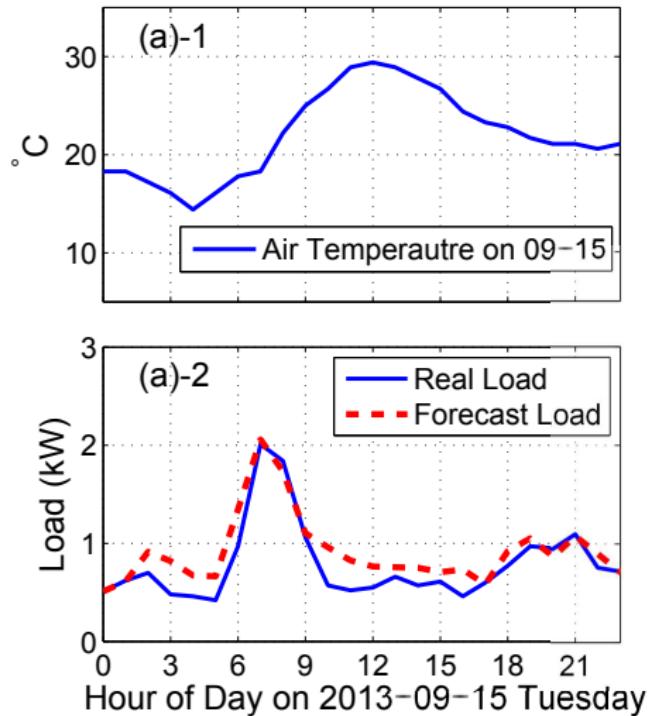


$$Y = f_{ANN}(X), \quad X = [T_a, D_w, T_d, L_h], \quad Y = [P_{dem,k+1}, \dots, P_{dem,k+m}]$$

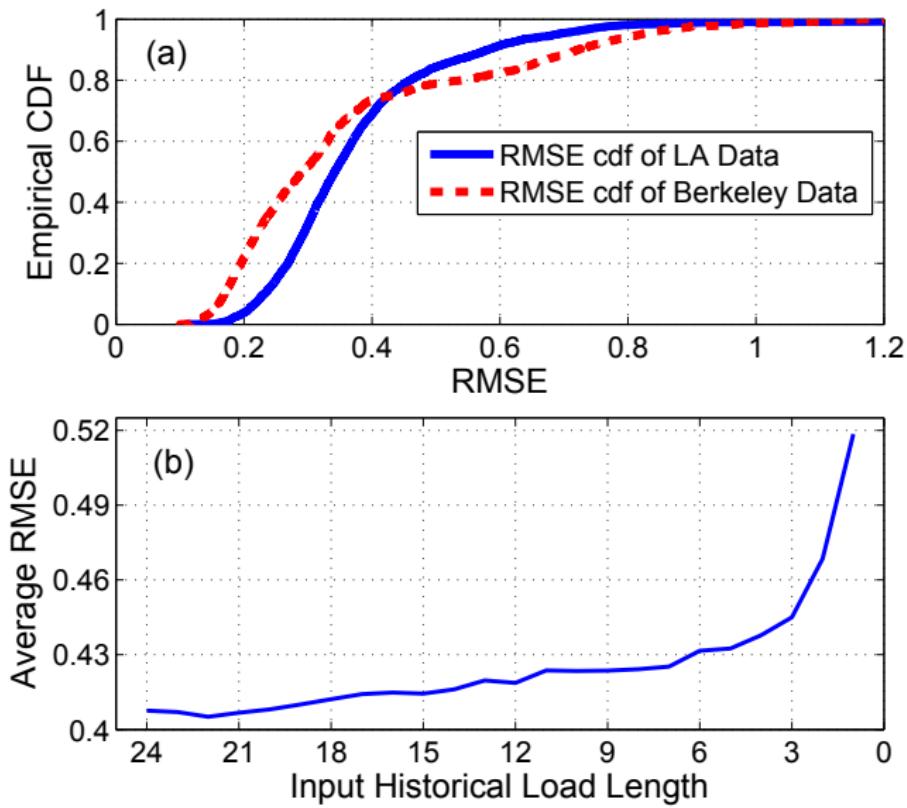
$$Y = f_{ANN}(X) = \sum_{i=1}^N \textcolor{blue}{a}_i \cdot H_i(\|X - \textcolor{blue}{C}_i\|)$$

$$H_i(\|X - \textcolor{blue}{C}_i\|) = \exp \left[ -\frac{1}{2\sigma_i^2} \|X - \textcolor{blue}{C}_i\|^2 \right]$$

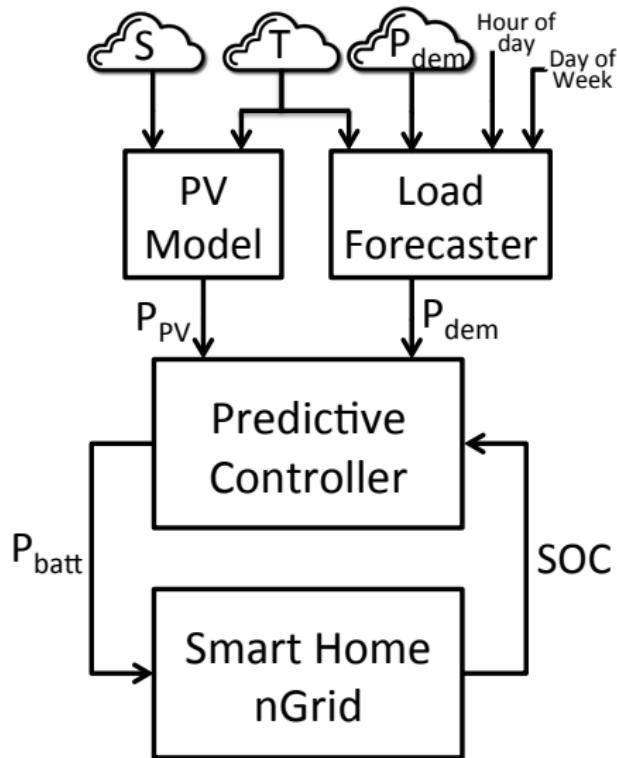
# Short-term Forecast of Home Load



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# Cloud-Enabled Control

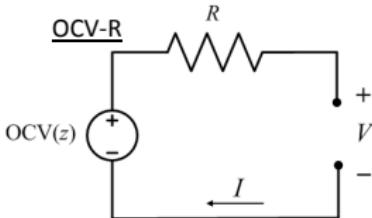


# Battery and Photovoltaic Cell Models

## battery

$$\frac{d}{dt} SOC(t) = -\frac{I_{batt}(t)}{Q},$$

$$P_{batt}(t) = V_{oc} I_{batt}(t) - I_{batt}^2(t) R_{in},$$



X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," *Journal of Power Sources*, vol. 198, pp. 359-367, 2012.

## photovoltaics

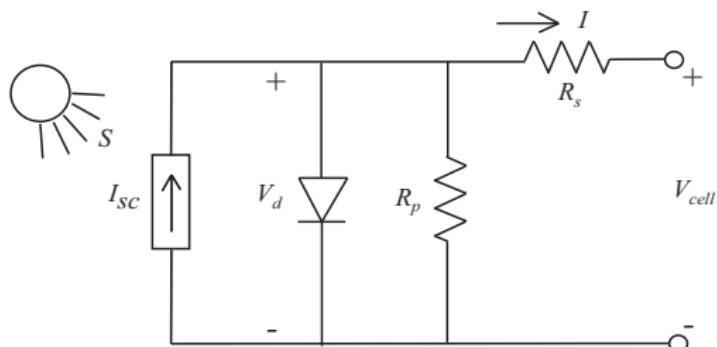
$$V_d = V_{cell} + I_{pv} R_s,$$

$$I = I_{sc} - I_s \left[ e^{(\frac{qV_d}{AkT_{pv}(t)})} - 1 \right] - \frac{V_d}{R_p},$$

$$I_s = I_{s,r} \left( \frac{T_{pv}(t)}{T_r} \right)^3 e^{\frac{qE_{bg}}{Ak} \left( \frac{1}{T_r} - \frac{1}{T_{pv}(t)} \right)},$$

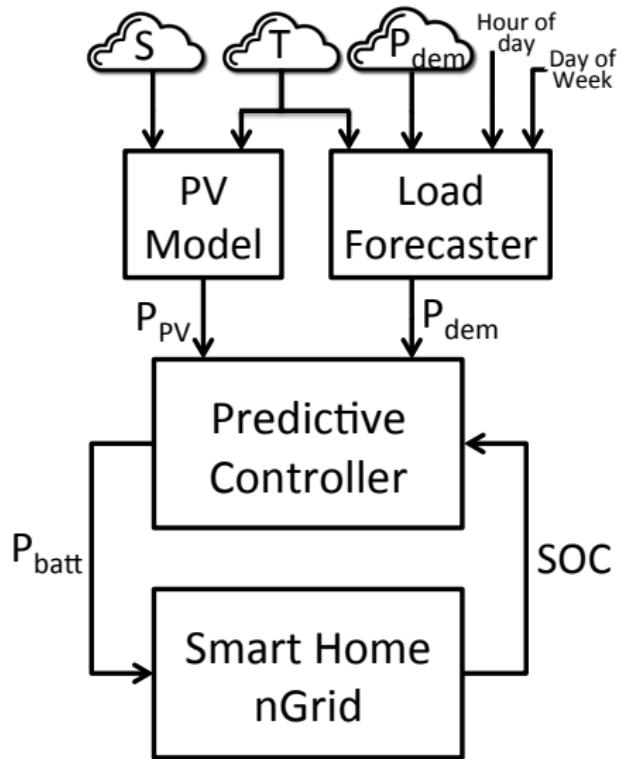
$$I_{sc} = [I_{sc,r} + K_I(T_{pv}(t) - T_r)] \frac{S_{pv}(t)}{1000},$$

$$P_{pv}(t) = n_{cell} V_{cell}(t) I(t)$$



G. Vachtsevanos and K. Kalaitzakis, "A hybrid photovoltaic simulator for utility interactive studies," *IEEE Transactions on Energy Conversion*, no. 2, pp. 227-231, 1987.

# Internet-based Data Feeds



# Internet-based Data Feeds

WEATHER UNDERGROUND | Maps & Radar | Severe Weather | News & Blogs | Photos & Video | Activities | More | Search & Recent Cities | [Like](#) | [g+1](#) | Share | Recent Cities | Berkeley, CA

Berkeley, CA | Alcatraz Ave | Change Station

Elev 138 ft 37.85 °N, 122.26 °W | Updated 4 sec ago

Clear | 63.5 °F | Feels Like 63.5 °F | Wind Variable | Gusts 0.0 mph | Rainfall | 0.0 in | Snow Depth | 0 in | 0 in | 0 in | UV | 0.0 out of 12 | Pollen | 2.80 out of 12 | Ozone | Good | PM2.5 | Moderate | Flu Activity | Not available.

Tomorrow is forecast to be **MUCH WARMER** than today.

Today | Yesterday  
High 74 | Low 61°F | High 71.8 | Low 59.7°F  
0% Chance of Precip. | Precip. 0 in

Sun & Moon  
7:03 am | 6:53 pm | Waxing Crescent, 44% visible

**Application Programming Interface (API) to receive data programmatically, in real-time**  
 $T(t)$ ,  $S(t)$

10-Day Weather Forecast

Graph | Table | Descriptive | Daily | Hourly | Customize

Tue 09/30	Wed 10/01	Thu 10/02	Fri 10/03	Sat 10/04	Sun 10/05	Mon 10/06	Tue 10/07	Wed 10/08	Thu 10/09
74°   61° Partly Cloudy 0 in	85°   63° Partly Cloudy 0 in	87°   65° Partly Cloudy 0 in	87°   65° Partly Cloudy 0 in	87°   60° Partly Cloudy 0 in	79°   59° Partly Cloudy 0 in	73°   59° Partly Cloudy 0 in	69°   58° Partly Cloudy 0 in	67°   59° Clear 0 in	68°   58° Clear 0 in

Temperature [°F] | 30.08 | 29.97

bcams | WunderMap | Nexrad | 10:29 PM PDT on September 30, 2014 (GMT -0700)

# Internet-based Data Feeds

Welcome Manuel Moura | My Account | Log Out | Saved Items  
中文 | TIẾNG VIỆT 🔍

## Application Programming Interface (API) to receive data programmatically, in real-time $P_{dem}(t)$

Home > Applications > My Account

My Account Profile

Account: 2-11-994-3140  
Rate: D-SDP  
Switch to accessible view

My Account Home  
My Bills & Payments  
Services  
My Green Button Data

Go Paperless!  
It's Convenient & Secure  
Sign Up Now ➔

Edison SmartConnect™  
**Check it out!**  
With the new My Account you can see your energy usage on an hourly basis.  
[Start Now ➔](#)

Hourly | Recent | Billed Months | Monthly Trend

Hourly  
Sep 29, 2014  
View another day: Day

Average Hourly Usage: 0.67 kWh      High Temp: 80°F

kWh

Hour	Usage (kWh)
12 AM	0.3
1	0.3
2	0.3
3	0.3
4	0.3
5	1.1
6	1.4
7	1.1
8	0.8
9	0.8
10	0.5
11	0.5
12	0.5
1	0.5
2	0.5
3	0.5
4	0.5
5	0.5
6	0.5
7	0.5
8	0.6
9	0.6
10	0.5
11	0.5

Roll over any bar to see more details

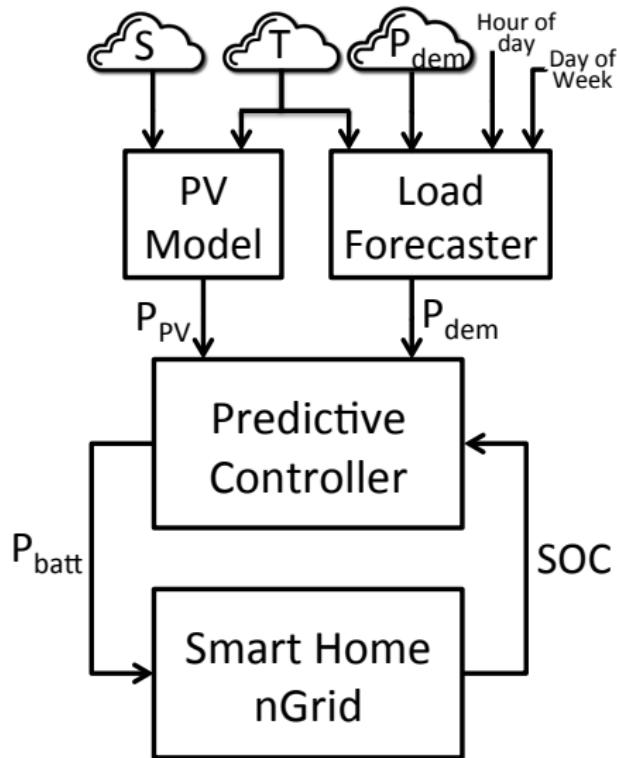
Weekday Weekend/Holiday

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# Cloud-Enabled Control



# Nonlinear MPC Formulation

$$\min \quad J_k = \int_{k\Delta t}^{(k+H_p)\Delta t} [\lambda_1 ElecPrice(t)P_{grid}(t) + \lambda_2 CO_2(t)P_{grid}(t)]^2 dt,$$

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s. to  $\dot{SOC} = -\frac{I_{batt}}{Q}$ , [Battery]

$$0 = V_{oc}I_{batt} - I_{batt}^2 R_{in} - P_{batt},$$

$$0 = h_{PV}(P_{pv}, S, T), \quad \text{[Photovoltaic]}$$

$$0 = P_{grid} + \eta_{dd}\eta_{da}P_{pv} + \eta_{da}P_{batt} - P_{dem}, \quad \text{[Pwr Balance]}$$

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$$\hat{d}((k+n)\Delta t) = f_{forecast}(d(k\Delta t), \dots, d((k-H_h)\Delta t)), \quad n = 1, \dots, H_p$$

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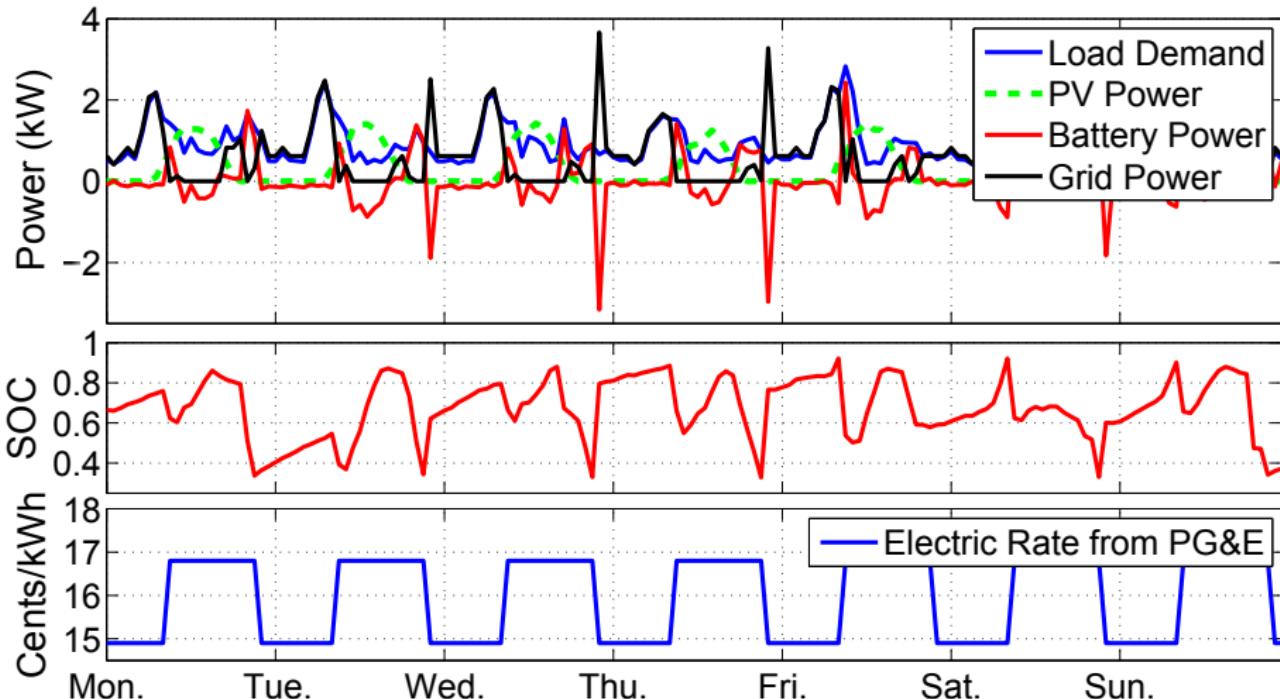
$$\hat{d}((k+n)\Delta t) = f_{forecast}(d(k\Delta t), \dots, d((k-H_h)\Delta t)), \quad n = 1, \dots, H_p$$

'state' =  $SOC$ , 'control' =  $P_{grid}$ , 'disturbance' =  $[P_{dem}, S_{pv}, T_{pv}]^T$

$$\Delta t = 1 \text{ hr}, \quad H_p = 6 \text{ hrs}, \quad H_h = 6 \text{ hrs}$$

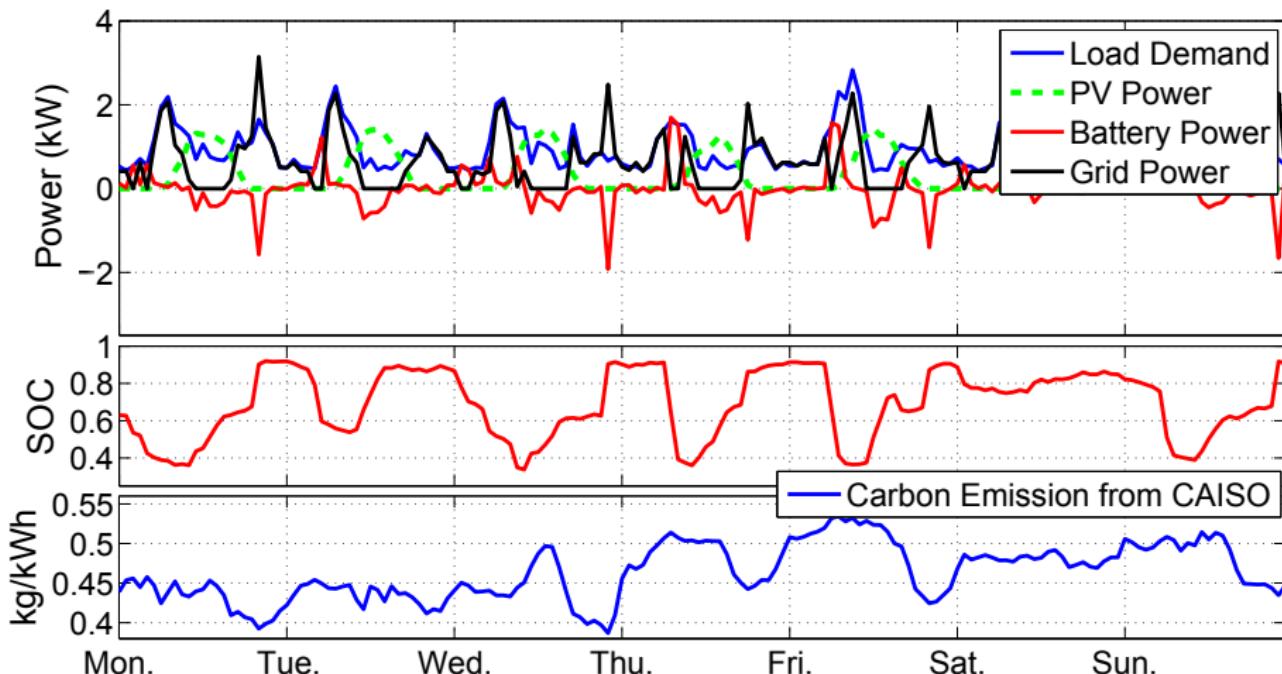
Solved via Dynamic Programming

# Model Predictive Control w/ Cloud-enabled Forecasts



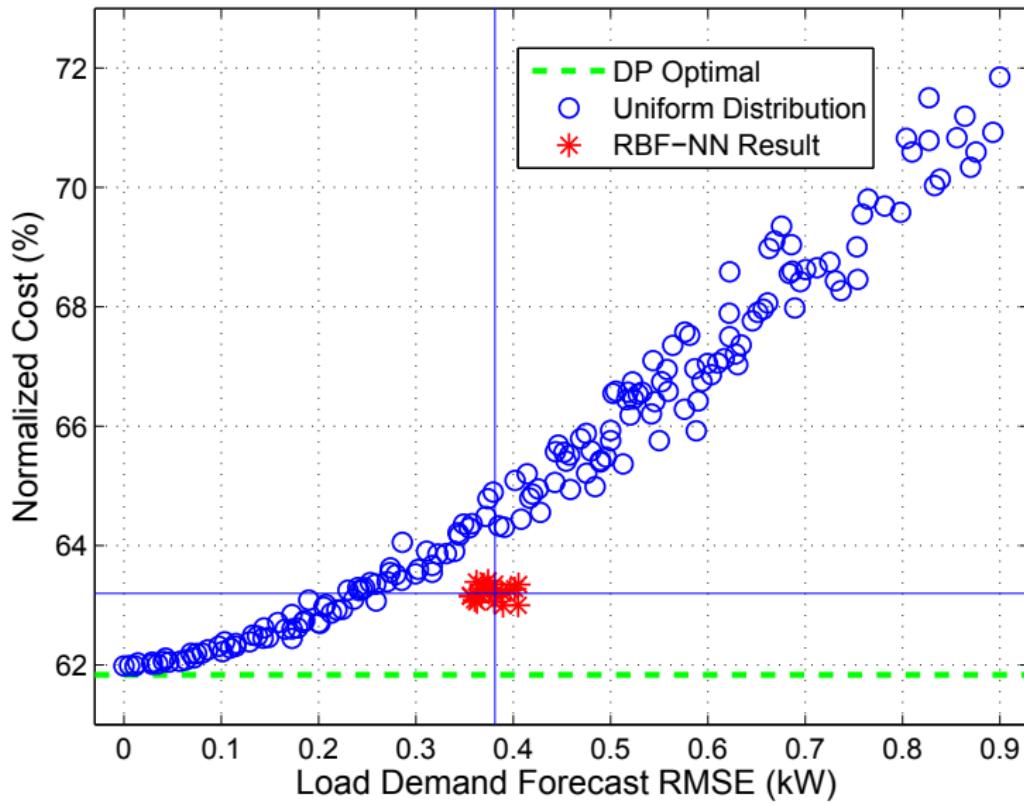
**Optimize for Grid Electricity Cost**

# Model Predictive Control w/ Cloud-enabled Forecasts



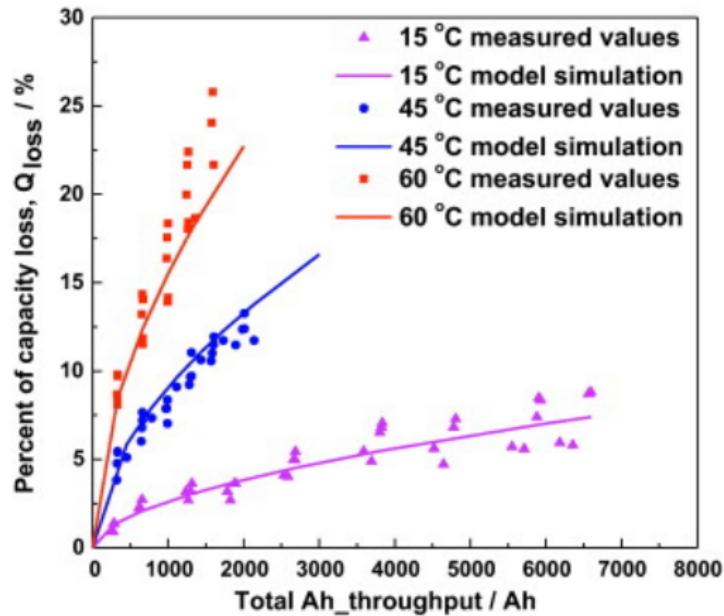
**Optimize for Marginal CO<sub>2</sub> Produced from Power Plants**

# Load Forecasting - how accurate is accurate enough?

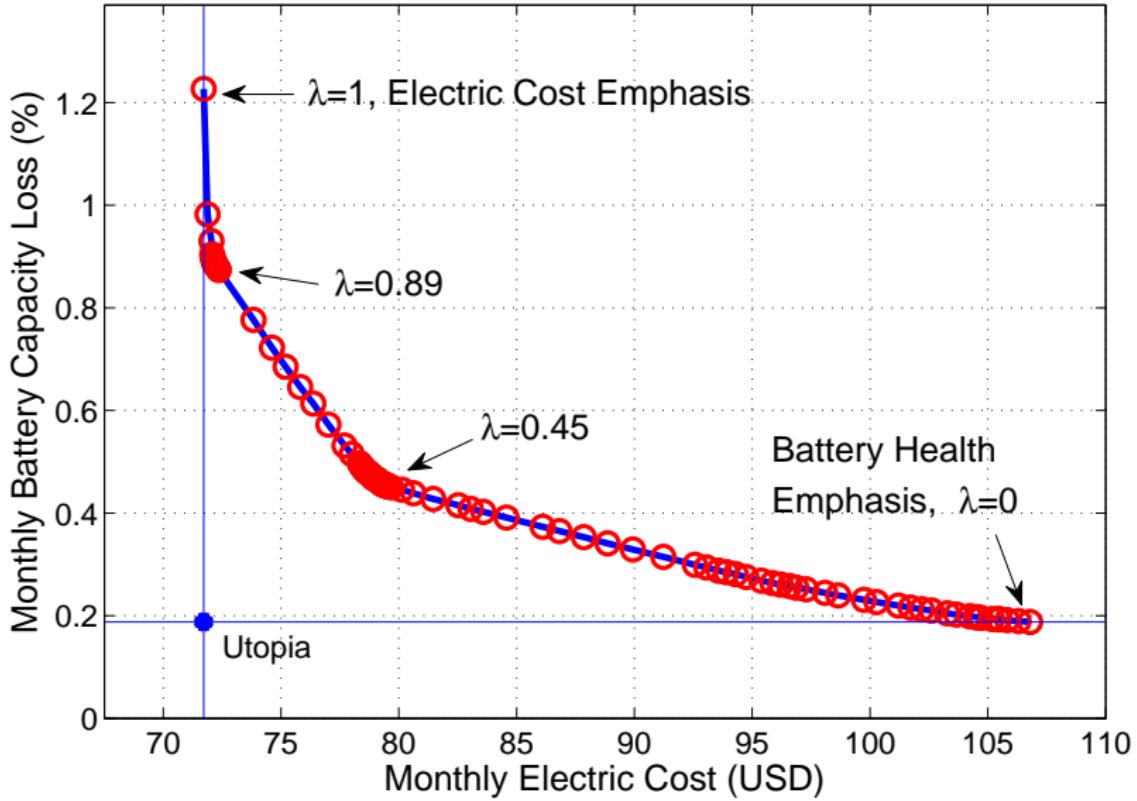


# Battery Health Aware

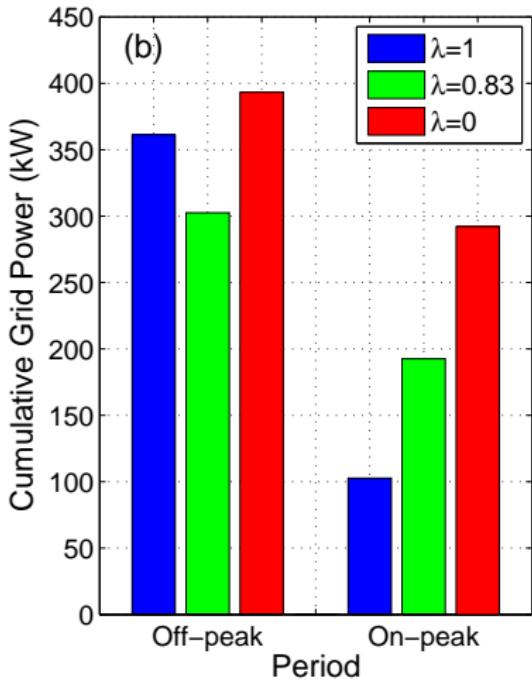
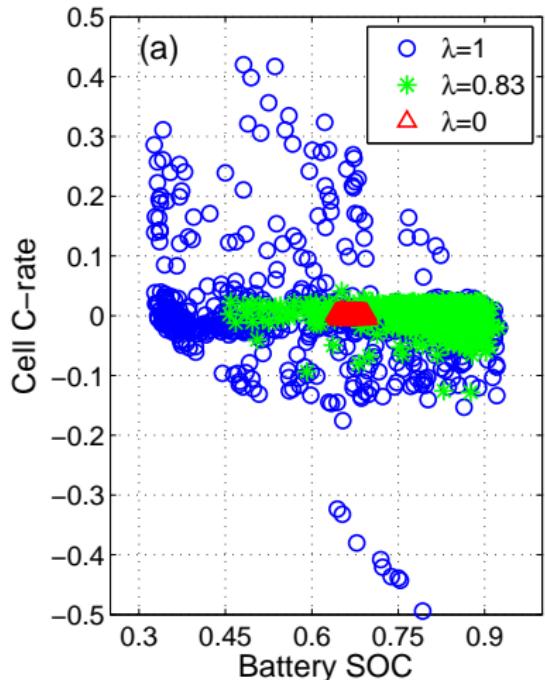
$$\min \quad J_k = \int_{k\Delta t}^{(k+H_p)\Delta t} [\lambda \cdot \text{ElecPrice}(u, t) + (1 - \lambda) \cdot Q_{loss}(u)]^2 \ dt$$



# Battery Health Aware



# Battery Health Aware

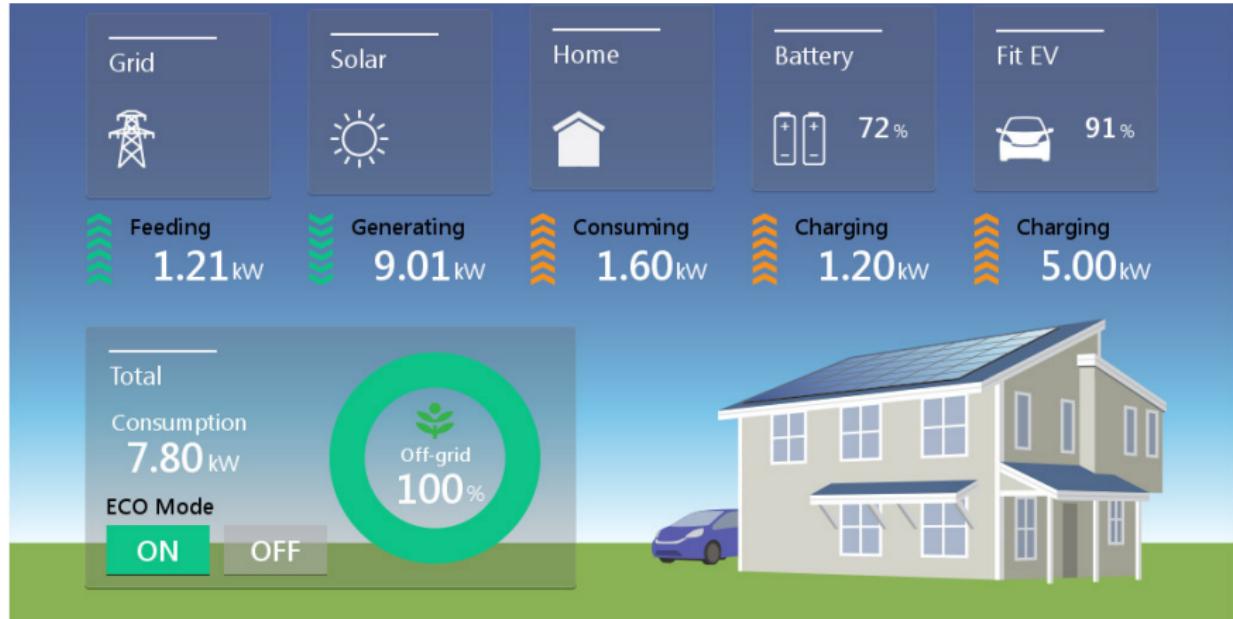


C. Sun, F. Sun, S. J. Moura, "Cloud Enabled Predictive Energy Management of a PV-Battery Smart Home Nanogrid" *in review*.

# Smart Home Demonstration Project @ UC Davis



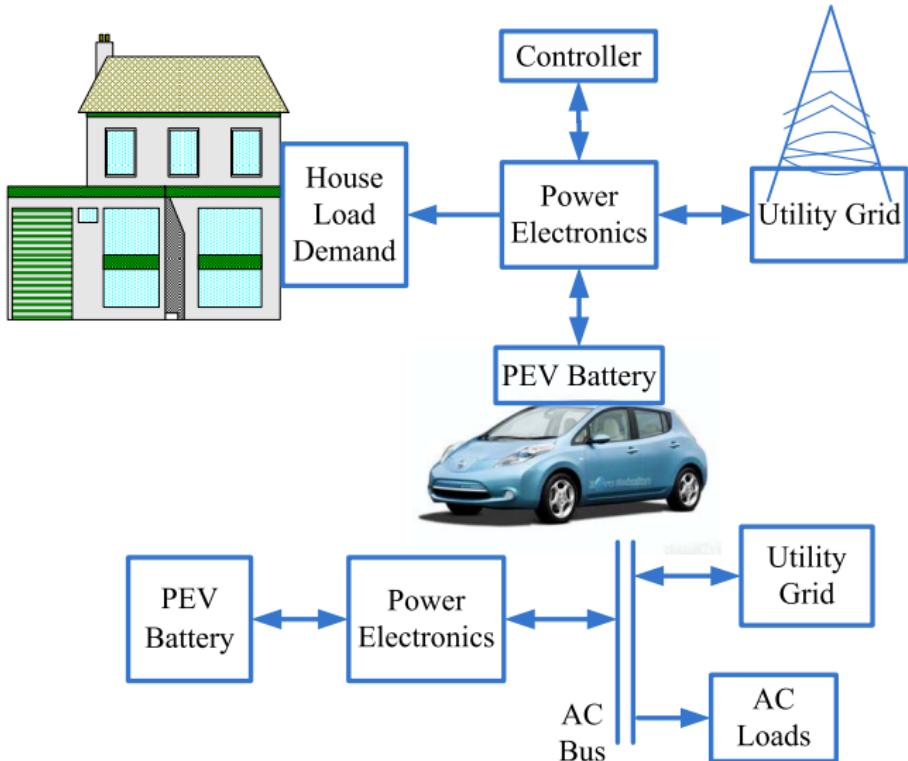
# Smart Home Demonstration Project @ UC Davis



# Outline

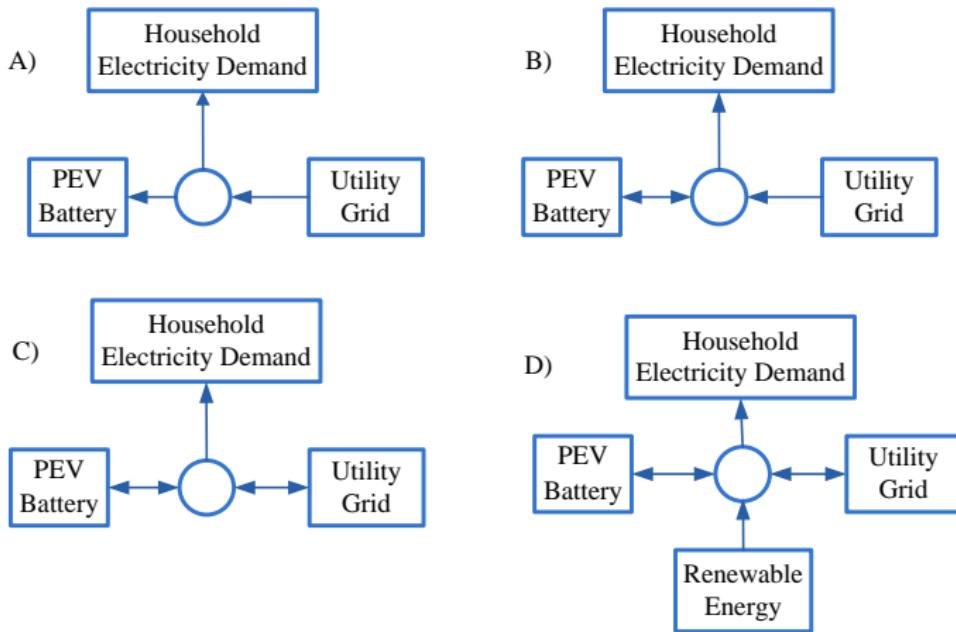
- 1 Forecasting Building Electric Demand
- 2 Residential Buildings with Solar & Storage
- 3 Integrating PEV Energy Storage with Buildings
- 4 Open Thoughts & Shameless Advertisements

# Stochastic PEV Energy Storage



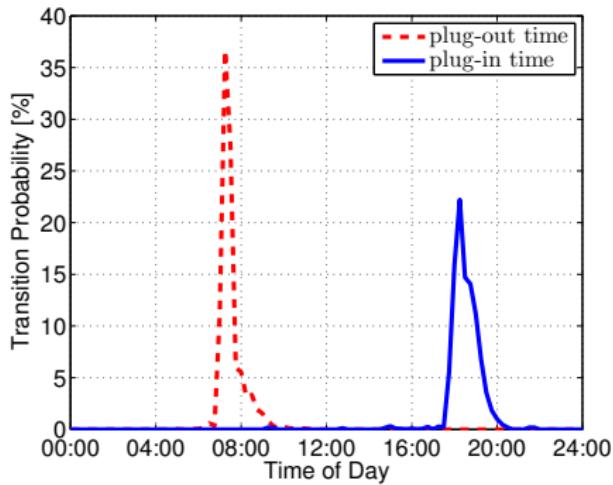
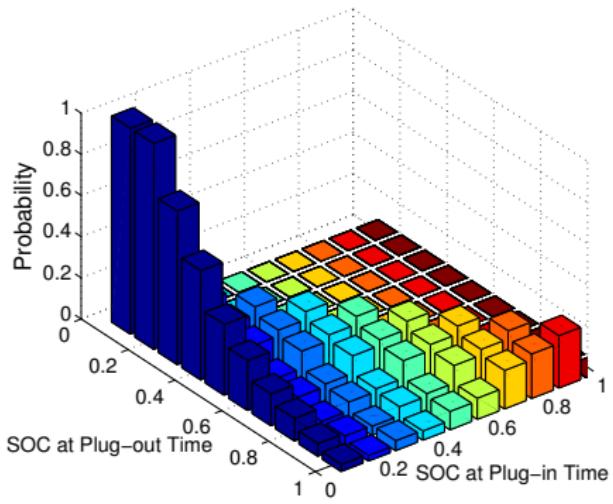
X. Wu, X. Hu, X. Yin, S. J. Moura, "Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage" *in review*.

# PEV-Home Nanogrid Operating Modes

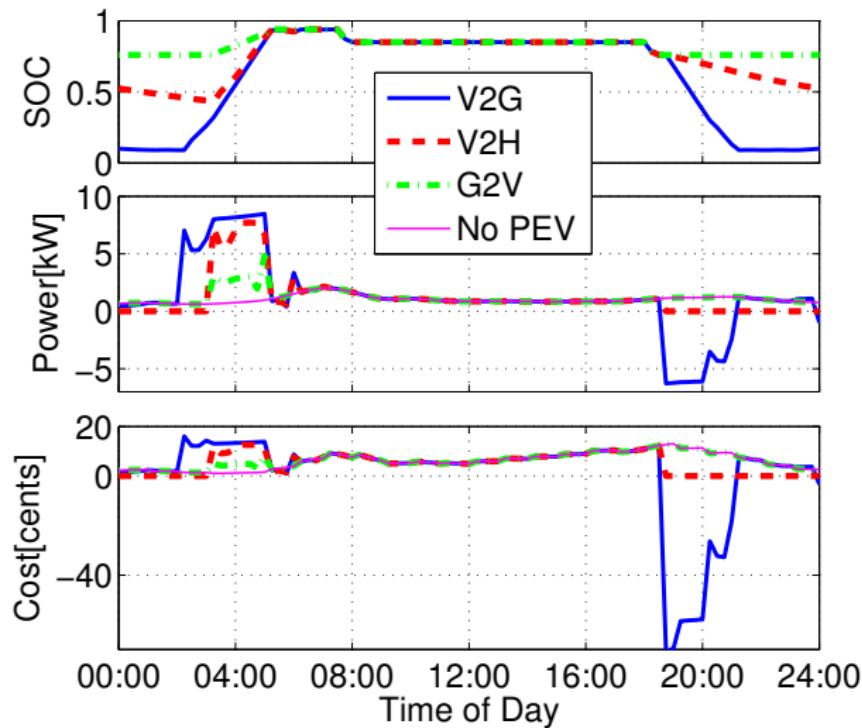


A) Grid-to-Vehicle (G2V); B) Vehicle-to-Home (V2H); C) Vehicle-to-Grid (V2G); D) V2G w/ PV

# Stochastic Mobility Needs

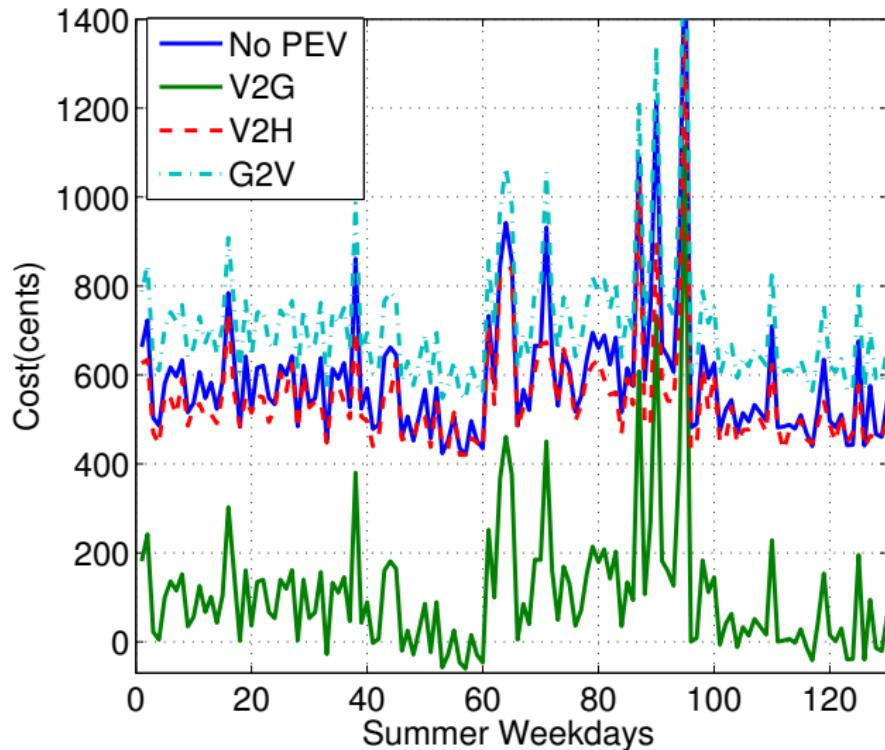


# Stochastic Dynamic Programming Results



X. Wu, X. Hu, X. Yin, S. J. Moura, "Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage" *in review*.

# Stochastic Dynamic Programming Results



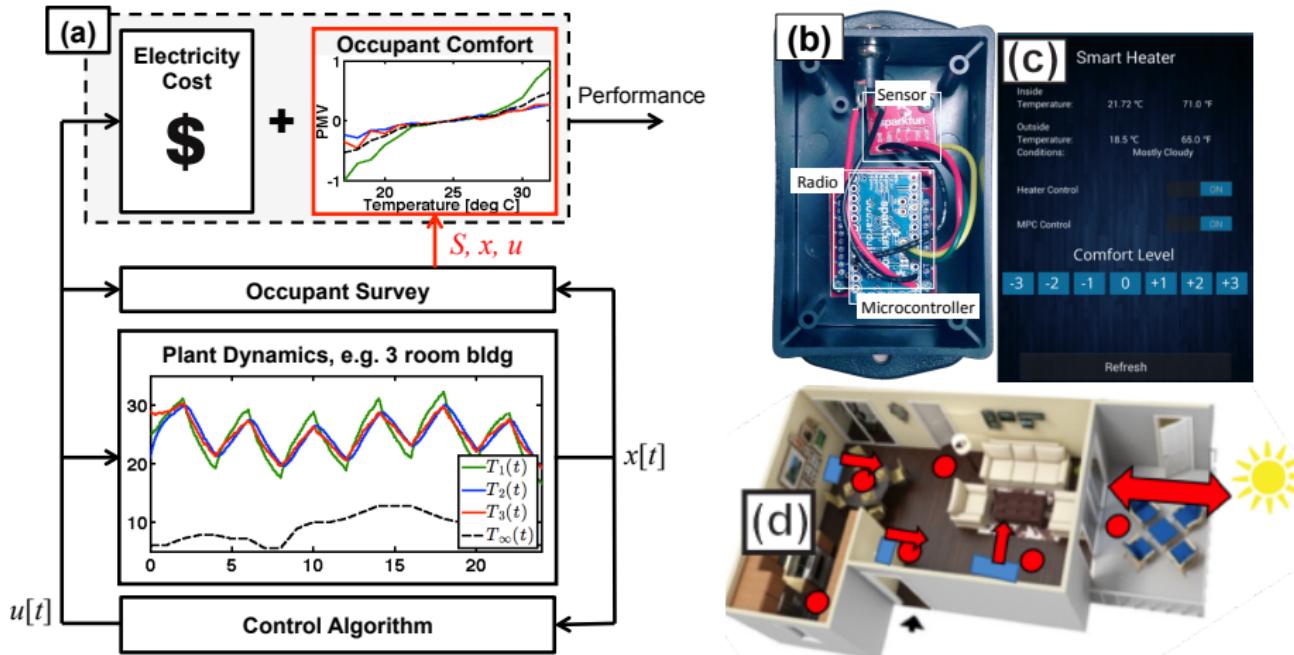
X. Wu, X. Hu, X. Yin, S. J. Moura, "Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage" *in review*.

# Outline

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# Explicit Consideration of Occupant Comfort + Cost

**Challenge:** How to quantify and learn occupant comfort?



# CE 186

## DESIGN OF CYBER-PHYSICAL SYSTEMS

Fall 2015 in Jacobs Hall (NEW!)



### Topics Include:

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

## Project-based Course on H/W, S/W and Energy

- Fleet of eScooters
- Indoor environmental sensing node
- Smart refrigerator
- Learn hardware, software, algorithms, big data, cloud-based computing
- Berkeley Energy and Climate Lectures Curriculum Innovation Award



## Sample Course Projects (S14/S15):

- Grey-box Model for a Single Room System Identification
- Temperature Prediction and Optimization Model for Night Flushing
- Development of a Stochastic Model to Predict Office Plug Load Profiles and Energy Consumption
- Home Energy Disaggregation
- Optimal Energy Control in an Residential Building
- Predictive Energy Demand Side Management for a Residential Photovoltaic and Battery Solution
- Energy Management in Commercial Buildings
- Building Materials for Decreased Boundary Losses to Ambient Environment
- Optimal Refrigeration Control for Soda Vending Machines
- Empirical Estimation of Electrified Heating Load Curves using Daily Natural Gas Consumption Data

# CE 295

## ENERGY SYSTEMS & CONTROL

Spring 2016: 3 units

Prof. Scott Moura

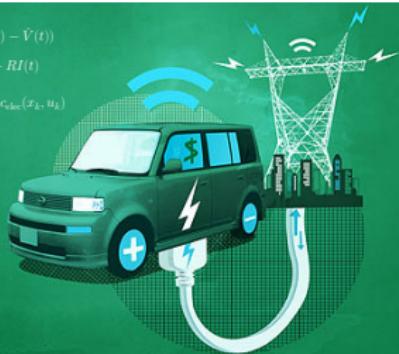
$$\dot{SOC}(t) = \frac{1}{Q}I(t) + \gamma(V(t) - \hat{V}(t))$$

$$\hat{V}(t) = OCV(\dot{SOC}) + RI(t)$$

$$\min_u J = \sum_{k=0}^N c_{\text{fuel}}(x_k, u_k) + c_{\text{elec}}(x_k, u_k)$$

$$V(t) = \frac{1}{2}x^T Q x$$

$$V(t) \leq -cV(t)$$



Topics Include:

- Energy Storage & Renewables
- Electrified Transportation & Bldg Energy
- Streaming data analytics
- Optimal control

# VISIT US!

Energy, Controls, and Applications Lab (eCAL)

[ecal.berkeley.edu](http://ecal.berkeley.edu)

[smoura@berkeley.edu](mailto:smoura@berkeley.edu)

