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

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eCAL
energy, controls, & applications lab

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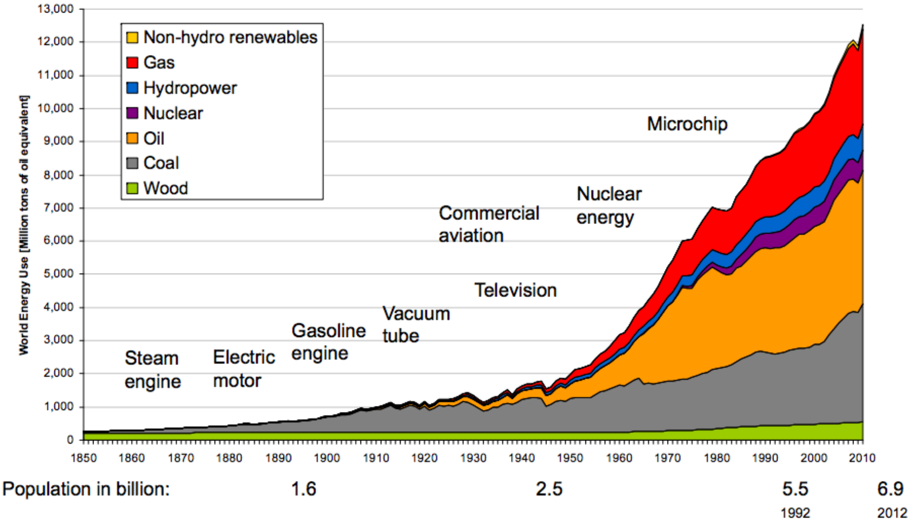
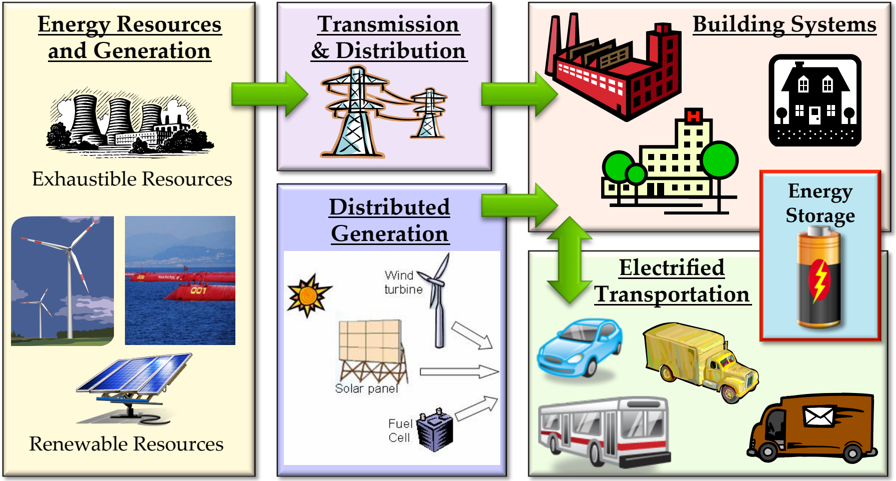
Colleagues	Fengchun Sun [Beijing Inst. Tech.],
	Jae Wan Park [UC Davis]

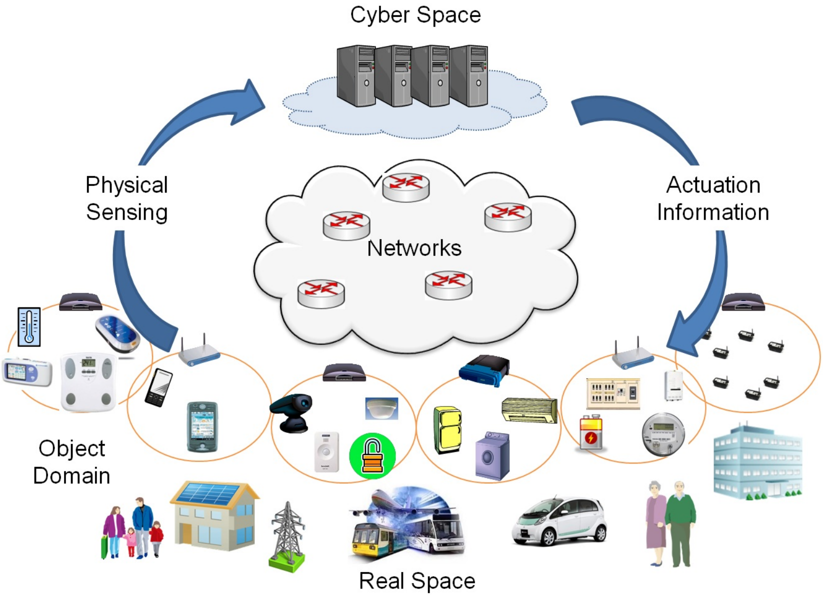


Compiled from data by Gruebler (1999), BP Statistical Review (2011) Nakicenovic & Gruebler (2000)

Vision for Future Energy Infrastructure



Cyber Physical Systems



Outline

The Electricity Demand Forecasting Problem

Needs: A generalized framework for forecasting electricity across a diversity of buildings, with only hourly consumption and meteorological data

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Some Motivating Facts

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

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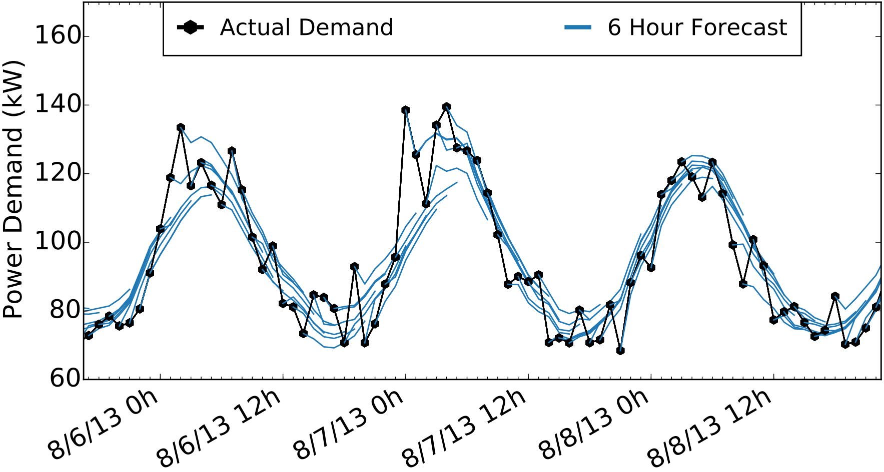
Punchline

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 $\hat{y}_s \in \mathbb{R}^m, \quad s = 1, \cdots, M$.

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 $s = 1, \cdots, M$.

Regression

Employ Least Squares with L_2 regularization (a.k.a. "Ridge" regression for scikit-learn users) to learn weights θ_s for $s = 1, \cdots, M$

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

$\theta_s \in \mathbb{R}$: weights for sub-model s, $\theta = [\theta_s]_{s=1,\cdots,M}$
$y_i \in \mathbb{R}^m$: i^{th} observed electricity demand
$\hat{y}_{s,i} \in \mathbb{R}^m$: i^{th} predicted electricity demand for sub-model s
$i = 1, \cdots, N$: where N is the number of data samples
λ : 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

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

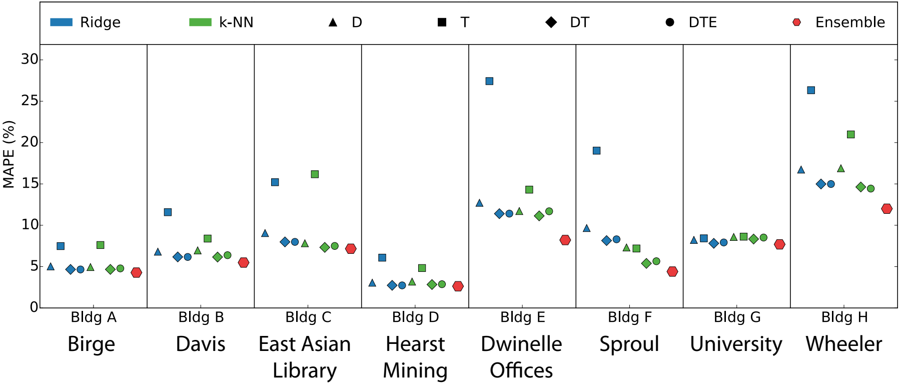
$\theta_{t,s} \in \mathbb{R}$: weights at time-step t, for sub-model s, $\theta_t = [\theta_{t,s}]_{s=1,\cdots,M}$
$y_{t-i} \in \mathbb{R}^m$: observed electricity demand at time step $t-i$
$\hat{y}_{s,t-i} \in \mathbb{R}^m$: predicted electricity demand for sub-model s, at time step $t-i$
$i = 1, \cdots, T$: where T is the length of the retrospective time horizon
λ : Weight for regularization penalty

Electricity Demand Forecasting

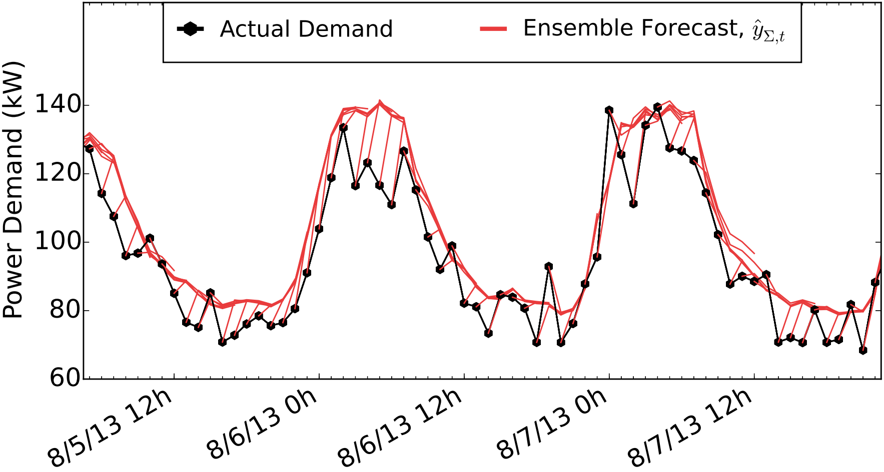
Train (offline): 8 buildings w/ 8 models each; data from 1/2013 to 6/2014

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

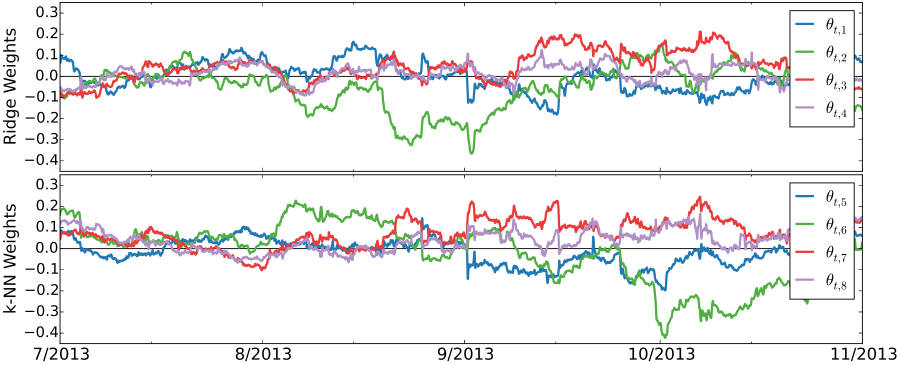
$$MAPE = 100\% \cdot \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_{i,\Sigma}}{y_i} \right|$$



Electricity Demand Forecasting | Dwinelle Offices

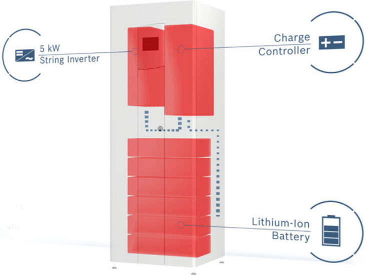


Electricity Demand Forecasting | Time-Varying $\theta_{t,s}$



Outline

Solar+Storage - An Emergent Market



The Building Solar+Storage Problem

Needs: Optimally manage energy flow between loads, solar, and storage.

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Some Motivating Facts

Policy	50% renewables in CA by 2030, 100% in Hawaii by 2045
Climate	2011 Tsunami in Japan $\rightarrow$ 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 $\leftrightarrow$ Engine Home Demand $\leftrightarrow$ Driver Power Demand Battery Storage $\leftrightarrow$ Battery Storage

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Data	Over 50M (43%) of US homes have smart meters
	Photovoltaics/Grid $\leftrightarrow$ Engine
Hybrid Vehicles	Home Demand $\leftrightarrow$ Driver Power Demand
	Battery Storage $\leftrightarrow$ Battery Storage

Punchline

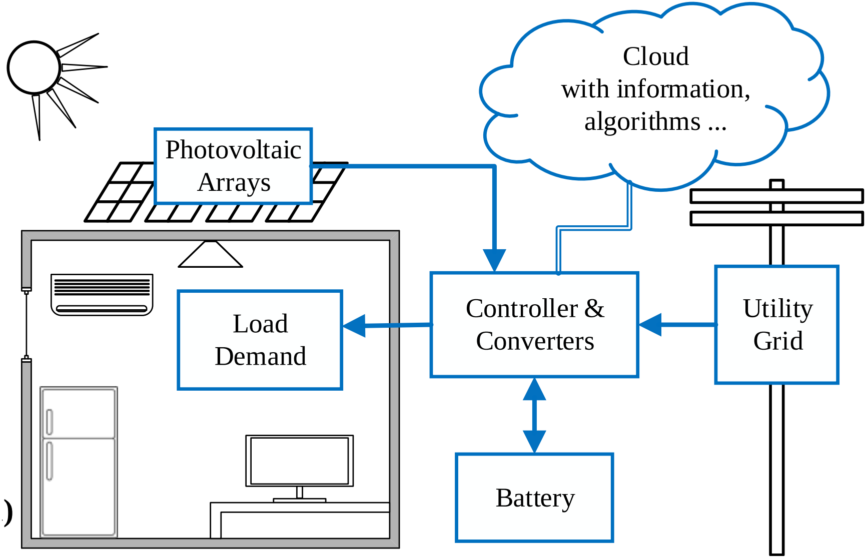
Apply & Extend $\sim$10 years of HEV Energy Management
Control Research to Building Solar+Storage

Features of Published Energy Management Frameworks for Buildings

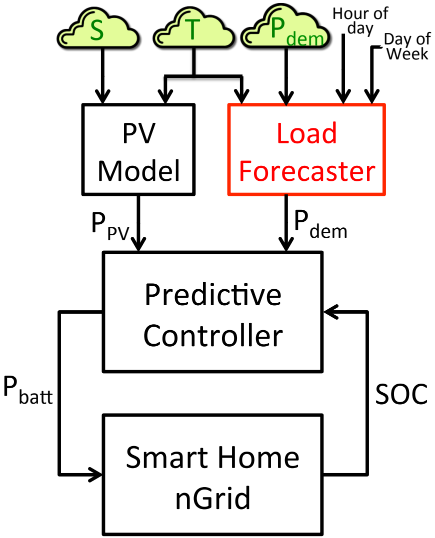
Features	[1]	[2]	[3]	[4]	[5]	[6]	[7]	Our Paper
Problem Formulation	Lin	Lin?	Lin	NL?	Lin	Lin	thermal circuit	NL
Solver	LP	DP	MILP	GA	MILP	MILP	LP?	DP
Battery Model	Lin	Lin (Int)	Lin	Lin (Int)	Lin (Int)	Lin (Int)	Lin (Int)	NL
Model Predictive Control							Y	Y
Load Forecast	Gauss Noise	Known	Known	Known		Known		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

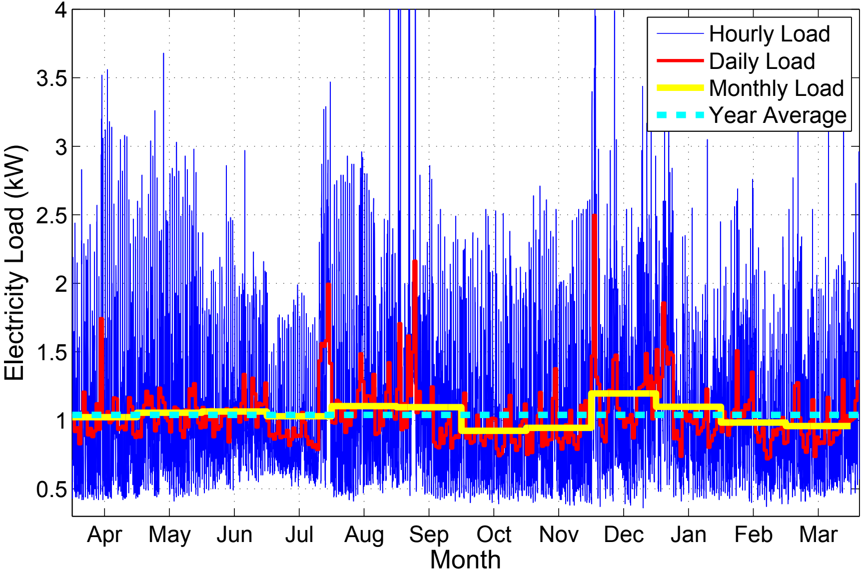
Residential Buildings with Solar & Storage



Predictive Controller with Load/Weather Forecasting



Single-Family Home Energy Patterns in LA



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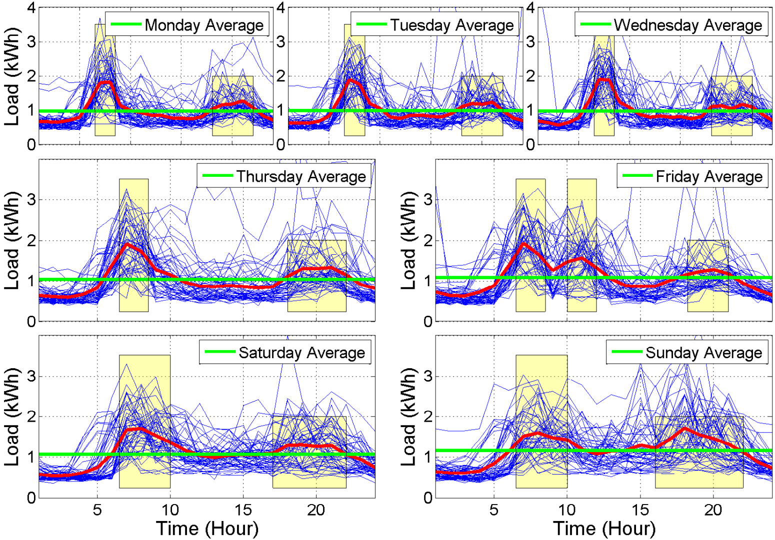

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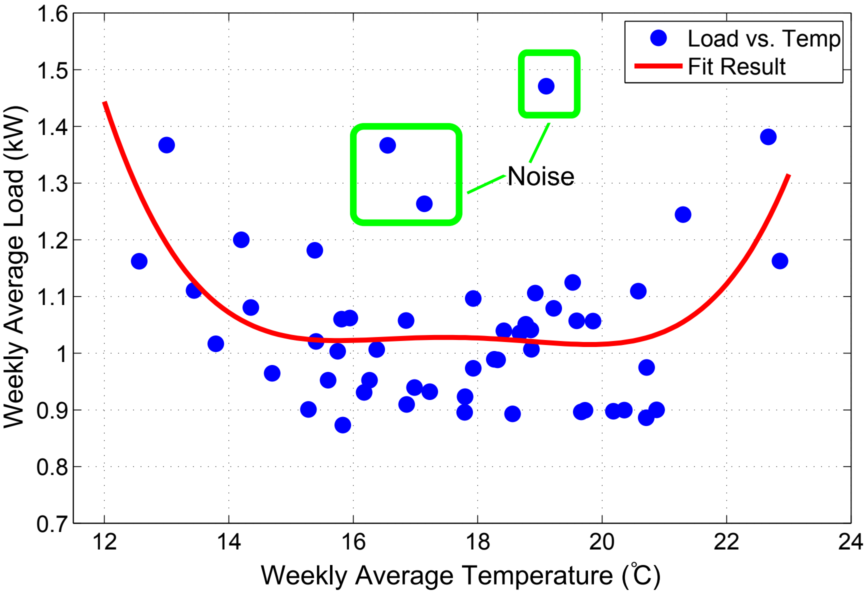
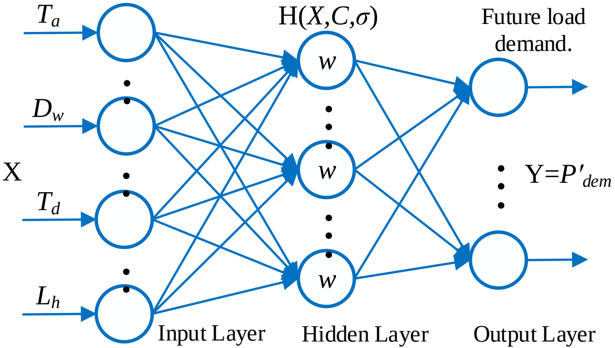


Artificial Neural Network (ANN)

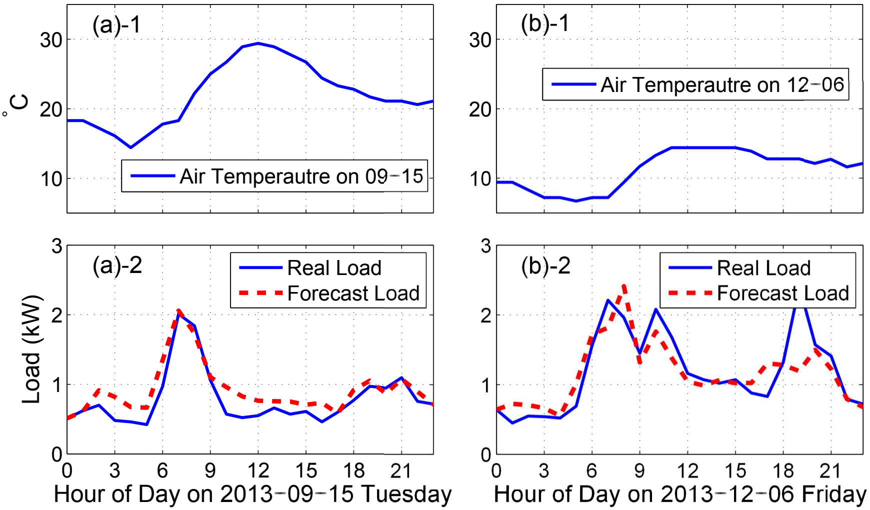


$$Y = f_{ANN}(X), \quad X = [T_a, D_w, T_d, L_h], \quad Y = [P_{dem,k+1}, \cdots, P_{dem,k+m}]$$

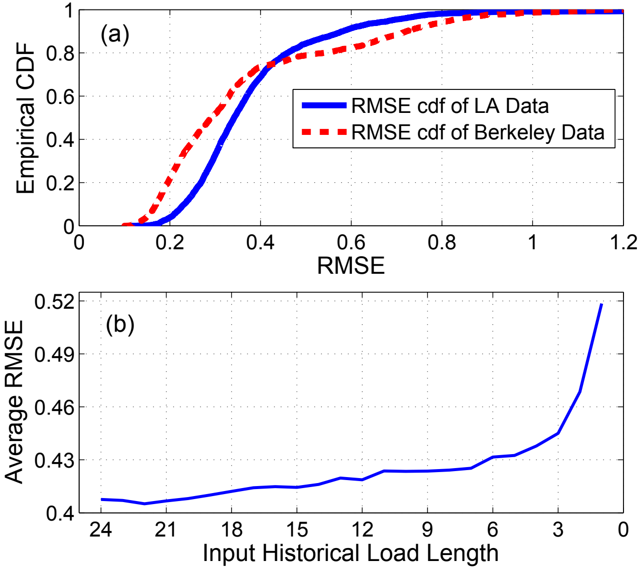
$$Y = f_{ANN}(X) = \sum_{i=1}^{N} a_i \cdot H_i(\|X - C_i\|)$$

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

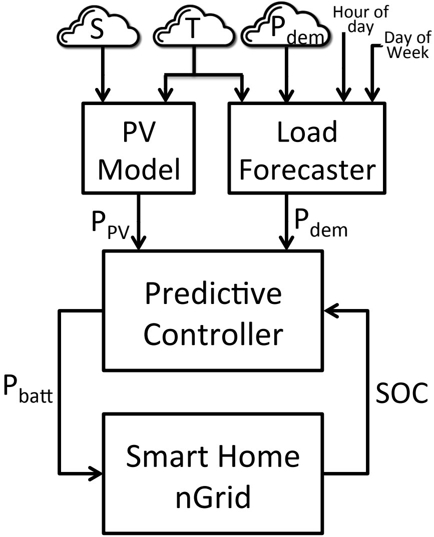
Short-term Forecast of Home Load



Short-term Forecast of Home Load

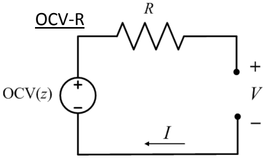


Cloud-Enabled Control



battery

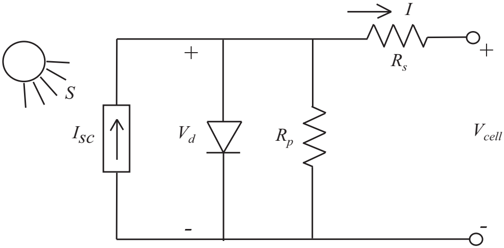
$$\frac{d}{dt}SOC(t) = -\frac{I_{batt}(t)}{Q},$$
$$P_{batt}(t) = V_{oc}I_{batt}(t) - I_{batt}^2(t)R_{in},$$



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.

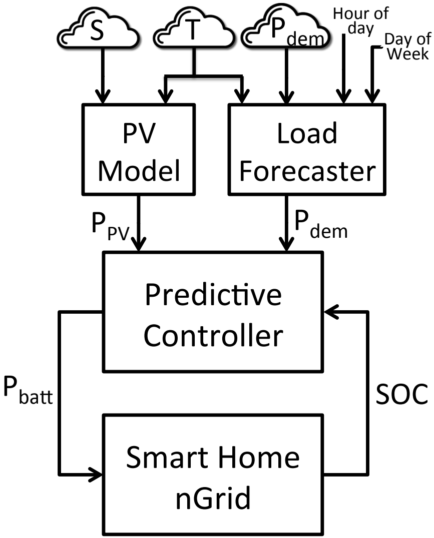
photovoltaics

$$V_d = V_{cell} + I_{pv}R_s,$$
$$I = I_{sc} - I_s\left[e^{\left(\frac{qV_d}{AkT_{pv}(t)}\right)} - 1\right] - \frac{V_d}{R_p},$$
$$I_s = I_{s,r}\left(\frac{T_{pv}(t)}{T_r}\right)^3 e^{\frac{qE_{bg}}{Ak}\left(\frac{1}{T_r} - \frac{1}{T_{pv}(t)}\right)},$$
$$I_{sc} = \left[I_{sc,r} + K_I(T_{pv}(t) - T_r)\right]\frac{S_{pv(t)}}{1000},$$
$$P_{pv}(t) = n_{cell}V_{cell}(t)I(t)$$



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



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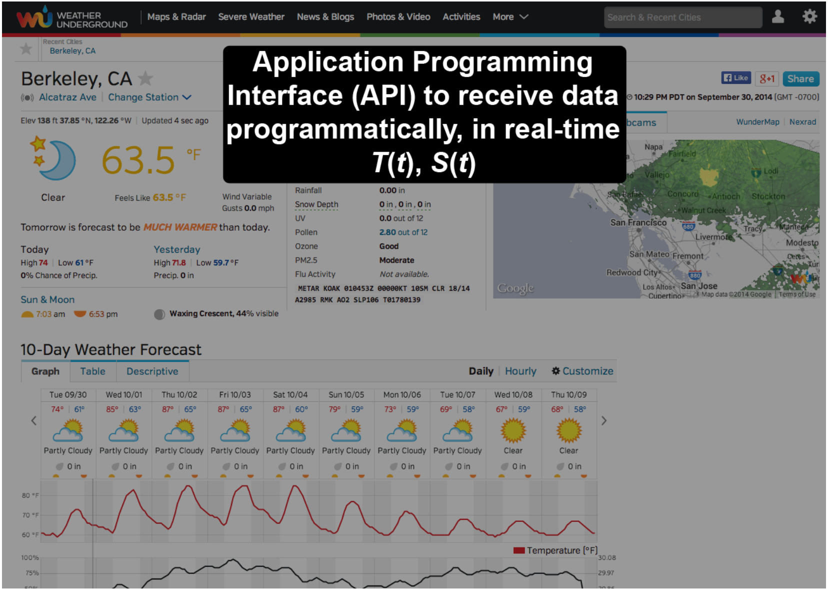

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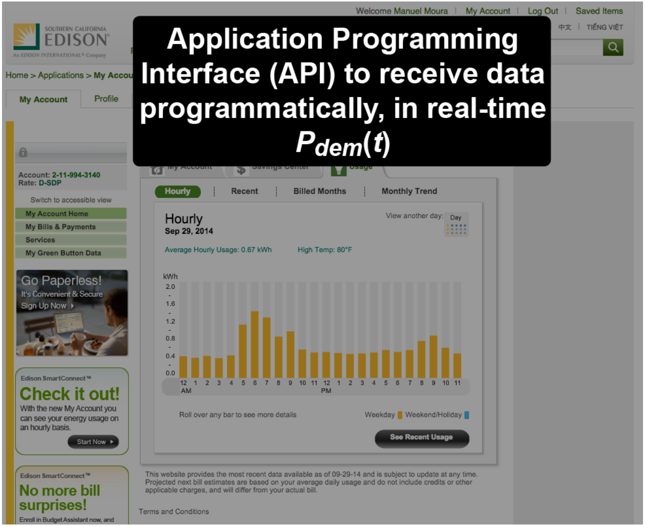
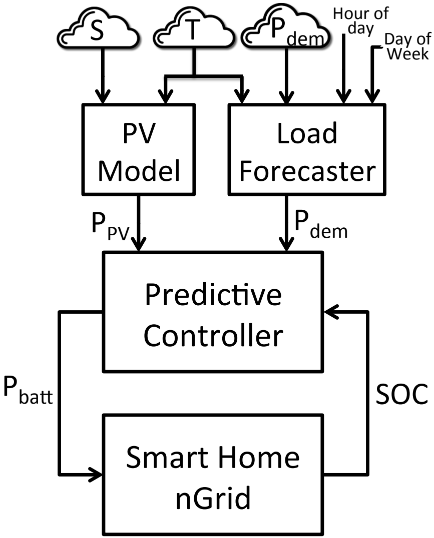


Application Programming Interface (API) to receive data programmatically, in real-time

$$P_{dem}(t)$$

Cloud-Enabled Control



Nonlinear MPC Formulation

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

Nonlinear MPC Formulation

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

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

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

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

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$$\text{SOC}^{\text{min}} \leq \text{SOC} \leq \text{SOC}^{\text{max}}, \ I_{batt}^{\text{min}} \leq I_{batt} \leq I_{batt}^{\text{max}},$$

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

Nonlinear MPC Formulation

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

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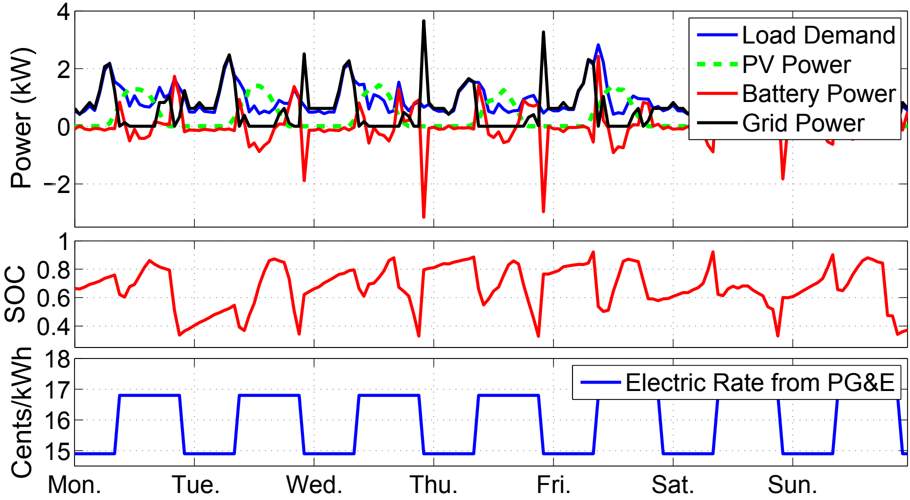
$$\hat{d}\left((k+n)\Delta t\right) = f_{forecast}\left(d(k\Delta t), \cdots, d((k-H_h)\Delta t)\right), \quad n = 1, \cdots, H_p$$

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

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

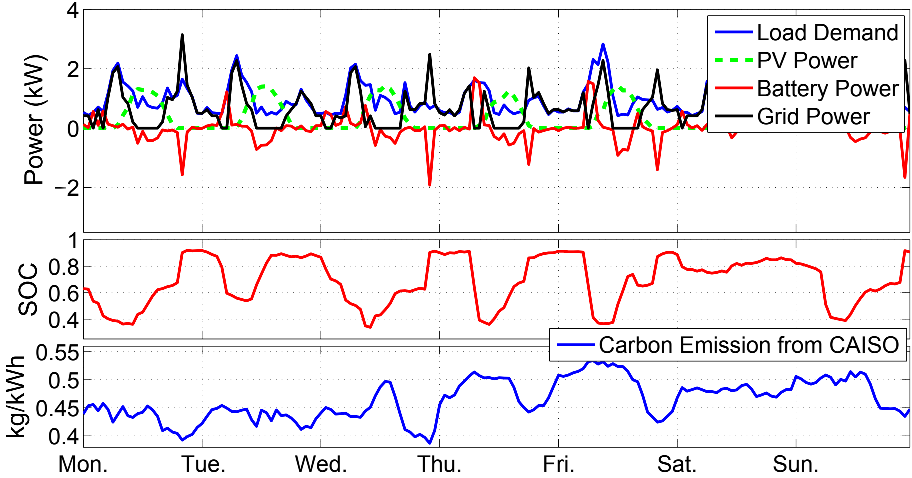
Solved via Dynamic Programming

Model Predictive Control w/ Cloud-enabled Forecasts



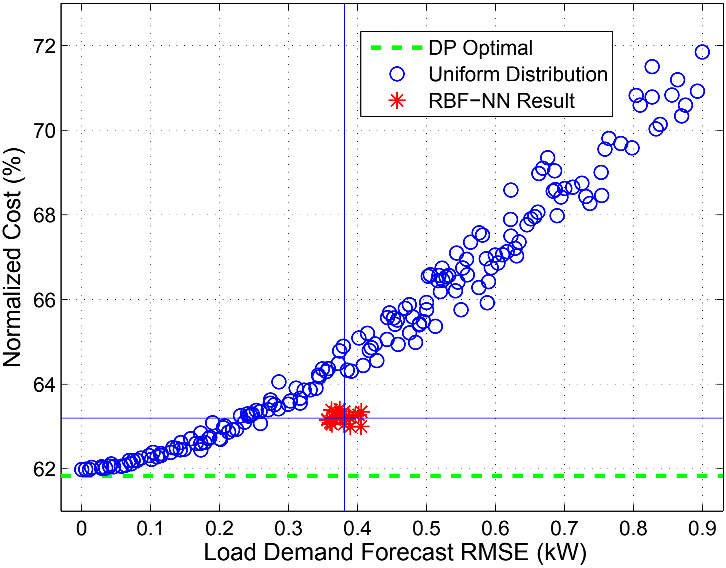
Optimize for Grid Electricity Cost

Model Predictive Control w/ Cloud-enabled Forecasts



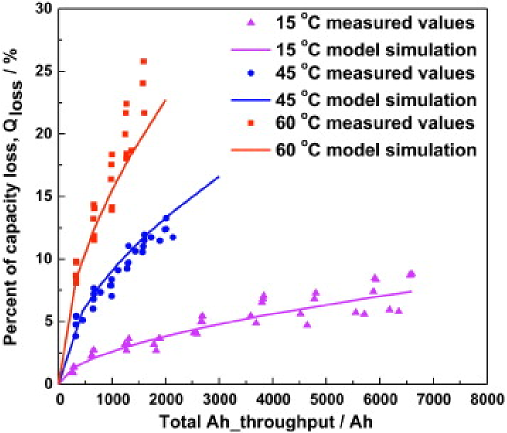
Optimize for Marginal CO_2 Produced from Power Plants

Load Forecasting - how accurate is accurate enough?



Battery Health Aware

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



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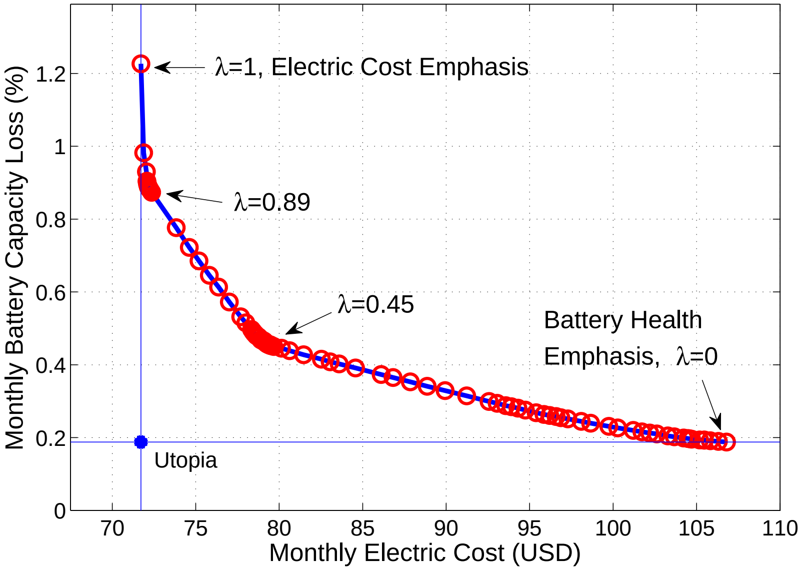

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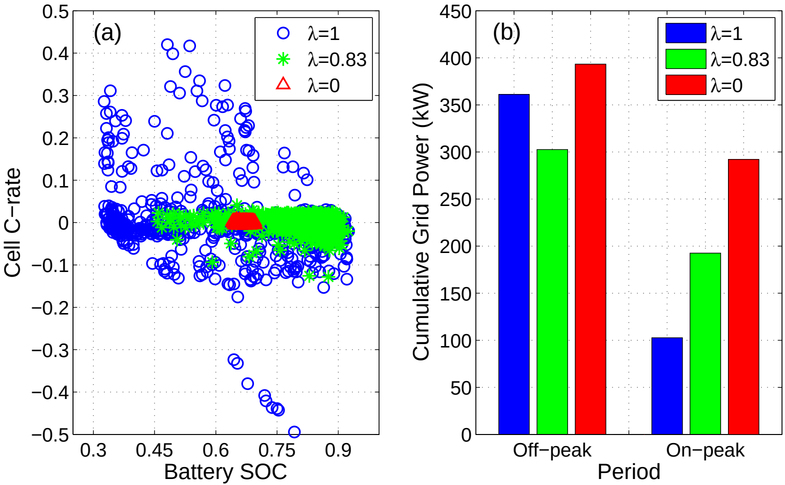

C. Sun, F. Sun, S. J. Moura, "Cloud Enabled Predictive Energy Management of a PV-Battery Smart Home Nanogrid" *in review*.

Smart Home Demonstration Project @ UC Davis

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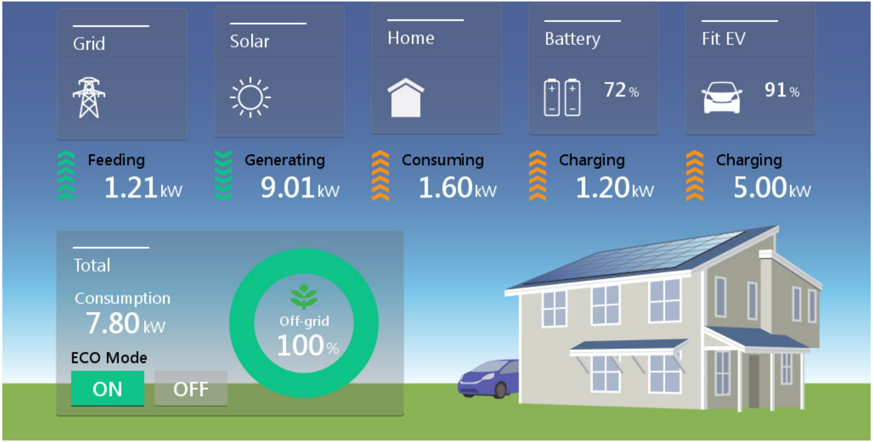
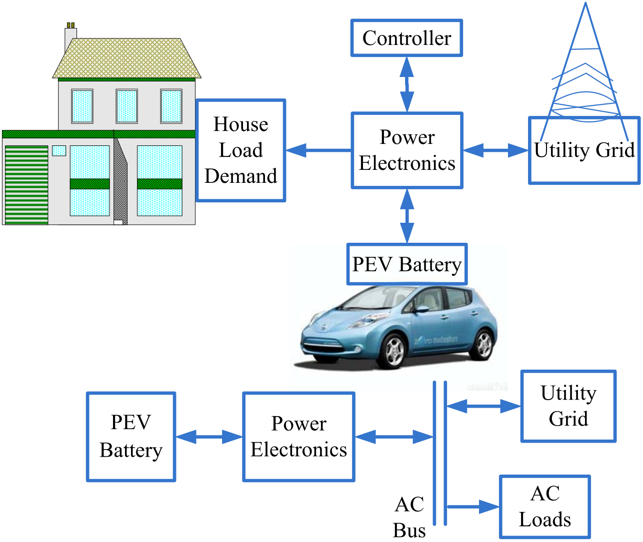


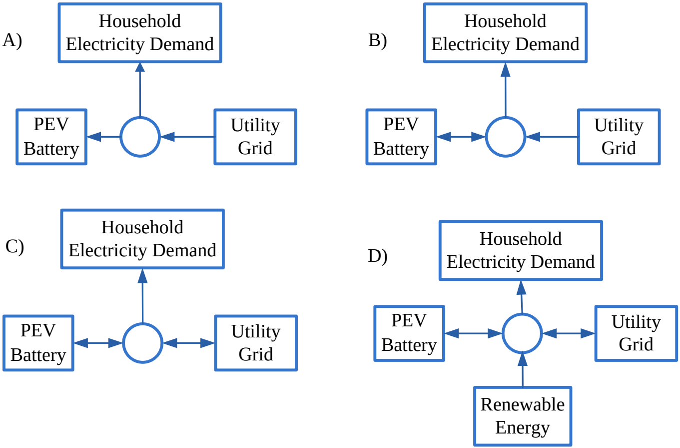
Outline

Stochastic PEV Energy Storage



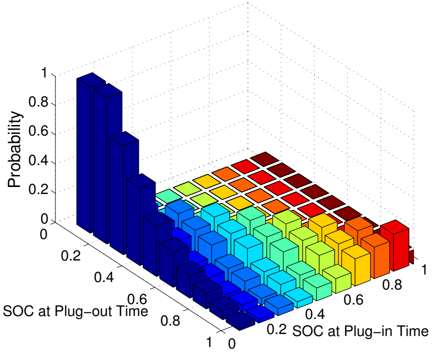
X. Wu, X. Hu, X. Yin, S. J. Moura, "Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage" *in review*.

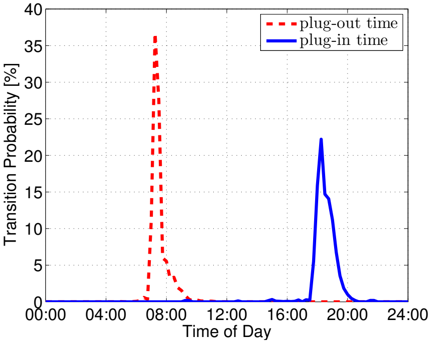
PEV-Home Nanogrid Operating Modes



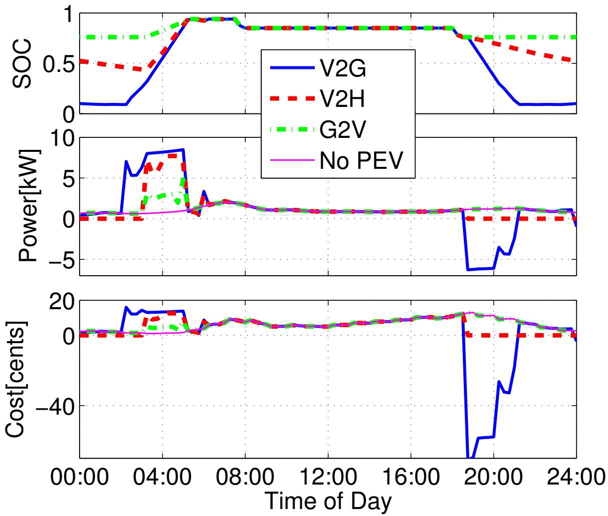
A) Grid-to-Vehicle (G2V); B) Vehicle-to-Home (V2H); C) Vehicle-to-Grid (V2G); D) V2G w/ PV

Stochastic Mobility Needs



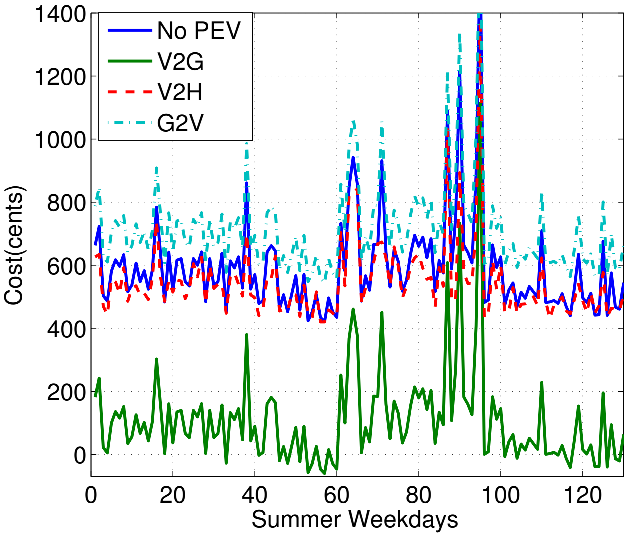


Stochastic Dynamic Programming Results



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

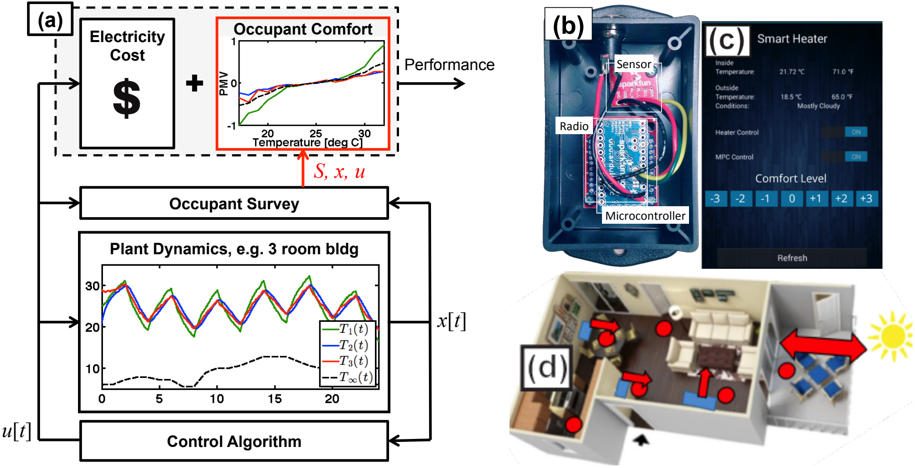


X. Wu, X. Hu, X. Yin, S. J. Moura, “Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage” *in review*.

Outline

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

Google App Engine

Sample Course Projects (S14/S15):

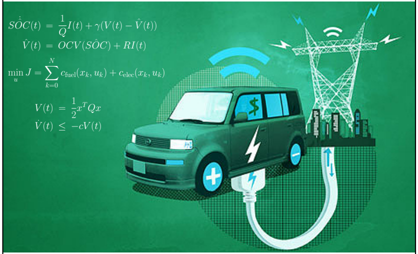
- Grey-box Model for a Single Room System Identification
- Temperature Prediction and Optimization Model for Night Flushing
- Development of a Stochastic Model to Predict Office Plug Load Profiles and Energy Consumption
- Home Energy Disaggregation
- Optimal Energy Control in an Residential Building
- 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



Topics Include:

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

VISIT US!

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