Energy and Controls:

Case Studies in Batteries, Buildings, and Flexible Loads

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TBSI ENE100 - Low Carbon Economics and Technologies

Tsinghua-Berkeley Shenzhen Institute

energy, controls, & applications lab

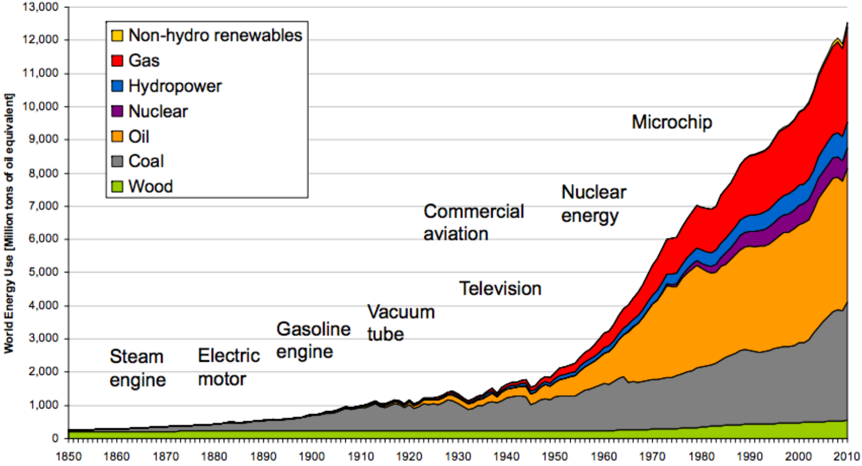
Download: http://ecal.berkeley.edu/pubs/talks/Moura-ENE100-EnergyMgmt.pdf

About me...

Professor Scott Moura
Postdoc - UC San Diego
PhD Mechanical Engineering - University of Michigan
MS Mechanical Engineering - University of Michigan
BS Mechanical Engineering - UC Berkeley

Research Interests: Control Systems, Estimation, Energy Storage, Electric Vehicles, Smart Grid

Selected Honors: Hellman Fellow, American Control Conference Best Student Paper Award (as advisor), UC Presidential Postdoctoral Fellow, NSF Graduate Research Fellow, ProQuest Distinguished Dissertation Award, Distinguished Leadership Award

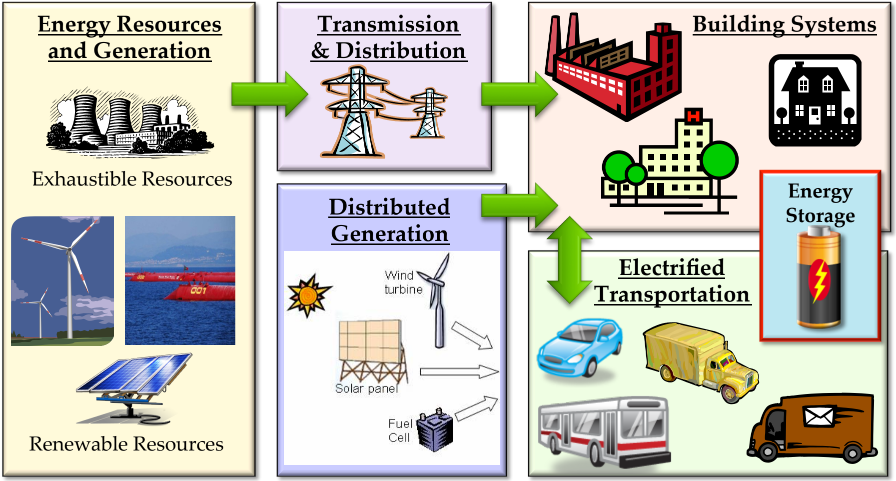


Population in billion: 1.6 2.5 5.5 6.9

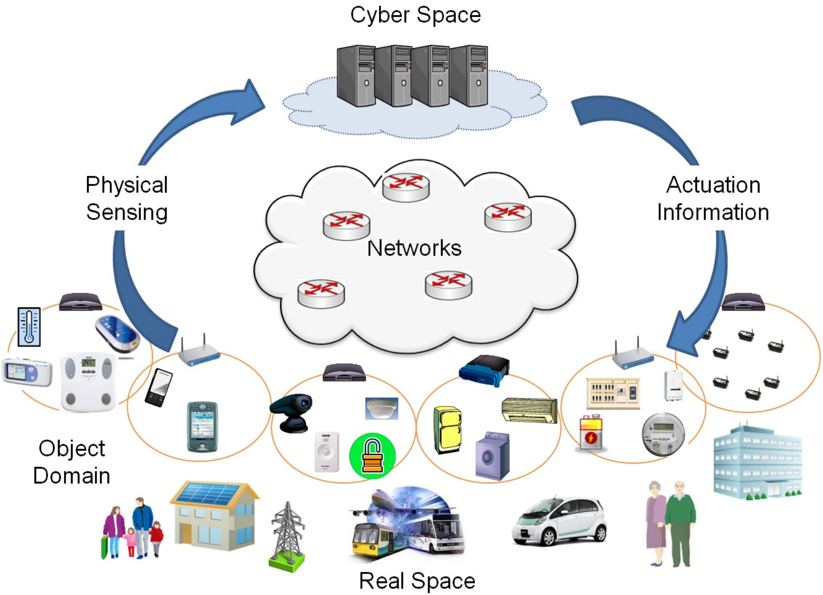
1992 2012

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

Vision for Future Energy Infrastructure



Cyber Physical Systems



Today's Schedule

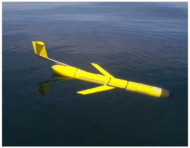
- STORAGE: Electrochemical-based Battery Controls
  - break: 9:15 – 9:20
- BUILDINGS: Predictive Energy Management w/ Solar + Storage
  - break: 10:05 – 10:15
- GRID: Modeling & Control of Flexible Loads

Outline

1. STORAGE: Electrochemical-based Battery Controls
   - Background & Battery Electrochemistry Fundamentals
   - Estimation and Control Problem Statements
   - State & Parameter Estimation
   - Constrained Optimal Control
2. BUILDINGS: Predictive Energy Management w/ Solar + Storage
   - Forecasting Building Electric Demand
   - Residential Buildings with Solar & Storage
   - Integrating PEV Energy Storage with Buildings
3. GRID: Modeling & Control of Flexible Loads
   - Thermostatically Controlled Loads (TCLS)
   - Plug-in Electric Vehicles (PEVs)

A Golden Era


IS-1
ST. JUDE MEDICAL
Sylmar, CA USA
ACCENT SR RF
PM1210 SSR
IS-1
ST. JUDE MEDICAL
Sylmar, CA USA
ANTHEM RF
PM3212 DDDRV



A Golden Era


ST. JUDE MEDICAL
Sylmar, CA USA
ACCENT SR RF
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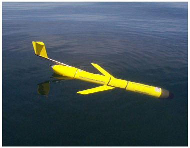

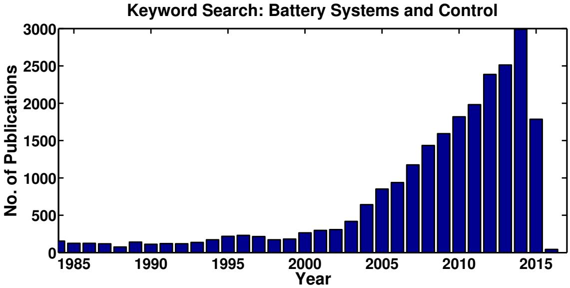
Keyword Search: Battery Systems and Control
No. of Publications
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500
1000
1500
2000
2500
3000
1985
1990
1995
2000
2005
2010
2015
Year

The Battery Problem

Needs: Cheap, high energy/power, fast charge, long life

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Reality: Expensive, conservatively design/operated, die too quickly

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Some Motivating Facts

EV Batts	1000 USD / kWh (2010)*
	485 USD / kWh (2012)*
	350 USD / kWh (2015)**
	125 USD / kWh for parity to IC engine
	Only 50-80% of available capacity is used
	Range anxiety inhibits adoption
	Lifetime risks caused by fast charging

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Reality: Expensive, conservatively design/operated, die too quickly

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Two Solutions

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

* Source: MIT Technology Review, "The Electric Car is Here to Stay." (2013)

** Source: Tesla Powerwall. (2015)

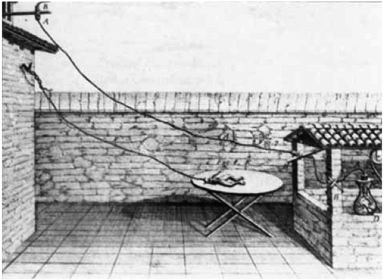
History

Luigi Galvani, 1737-1798,
Physicist, Bologna, Italy

"Animal electricity"
Dubbed "galvanism"

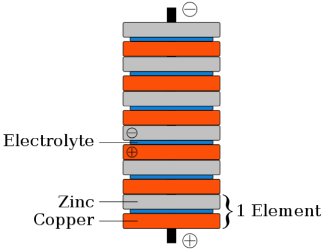
First foray into
electrophysiology

Experiments on frog legs



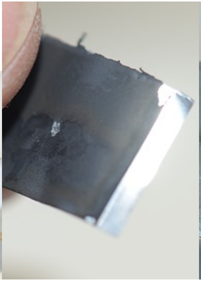
Alessandro Volta, 1745-1827
Physicist, Como, Italy

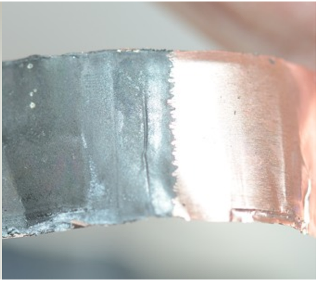
Voltaic Pile



Monument to Volta in Como

Cell Assembly - Jelly Roll





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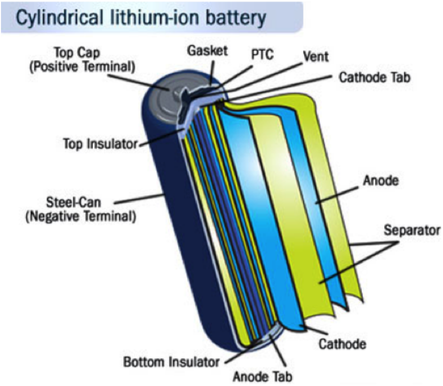
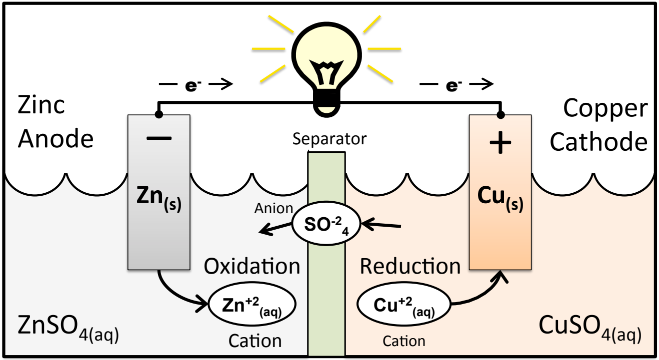


Battery Cell Anatomy

Principles of Operation



Anode Half Cell:

$$Zn_{(s)} \rightarrow Zn^{2+}_{(aq)} + 2e^-$$

Cathode Half Cell:

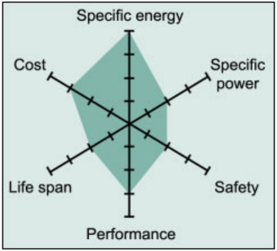
$$Cu^{2+}_{(aq)} + 2e^- \rightarrow Cu_{(s)}$$

Total Rxn:

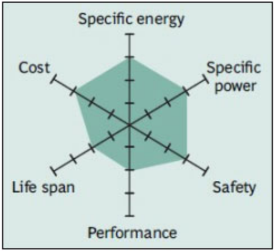
$$Zn_{(s)} + Cu^{2+}_{(aq)} \rightarrow Zn^{2+}_{(aq)} + Cu_{(s)}$$

Comparison of Lithium Ion (Cathode) Chemistries

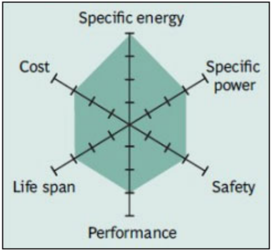
Lithium Cobalt Oxide ($LiCO_2$)



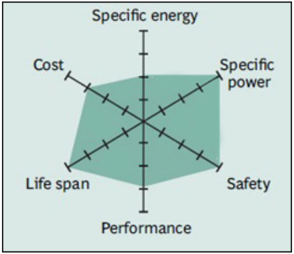
Lithium Manganese Oxide ($LiMn_2O_4$)



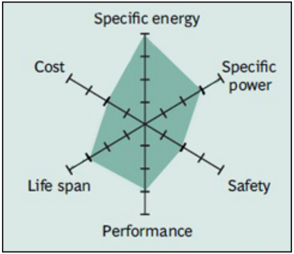
Lithium Nickel Manganese Cobalt Oxide ($LiNiMnCoO_2$)



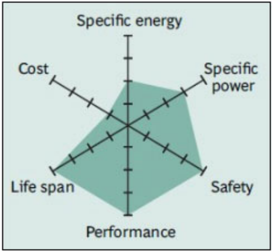
Lithium Iron Phosphate ($LiFePO_4$)



Lithium Nickel Cobalt Aluminum Oxide ($LiNiCoAlO_2$)

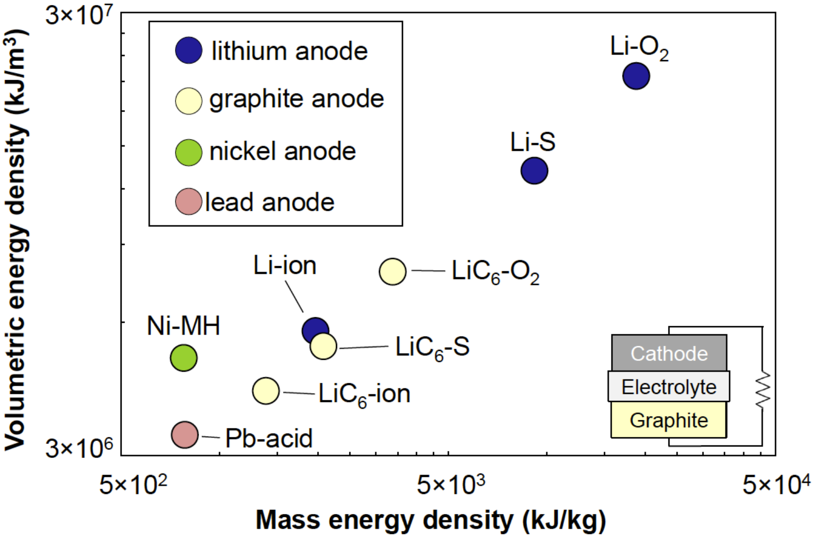


Lithium Titanate ($Li4Ti_5O_{12}$)



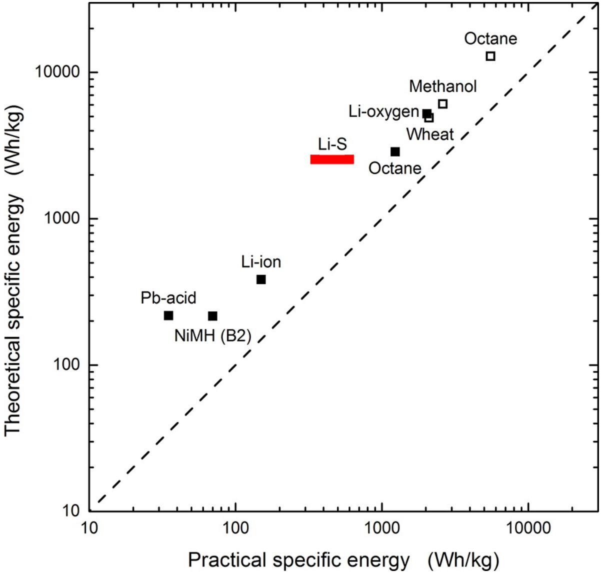
Source: `http://batteryuniversity.com/learn/article/types_of_lithium_ion`

Energy Density

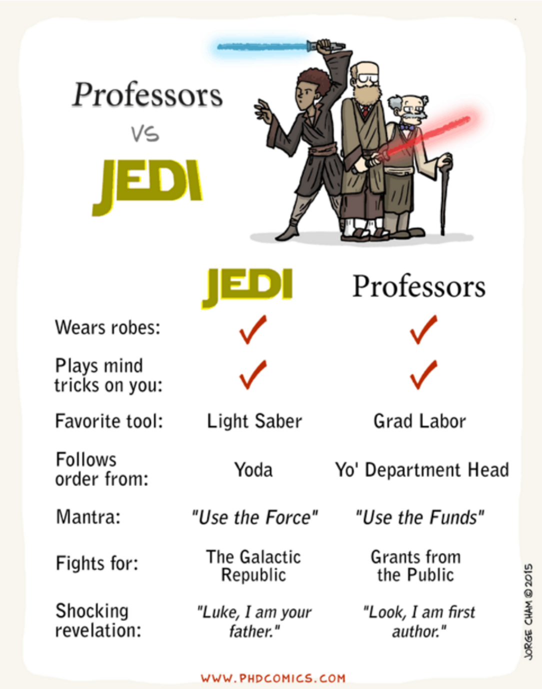


Source: Katherine Harry & Nitash Balsara, UC Berkeley

Energy Density



N. P. Balsara, and J. Newman, “Comparing the Energy Content of Batteries, Fuels, and Materials”, Journal of Chemical Education, 90 (2013), 446-52.


Professors
VS
JEDI
JEDI
Professors
Wears robes:
Plays mind tricks on you:
Favorite tool:
Light Saber
Grad Labor
Follows order from:
Yoda
Yo' Department Head
Mantra:
"Use the Force"
"Use the Funds"
Fights for:
The Galactic Republic
Grants from the Public
Shocking revelation:
"Luke, I am your father."
"Look, I am first author."
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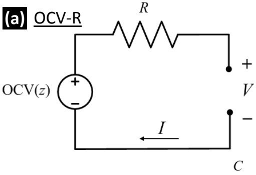
Equivalent Circuit Model

(a) OCV-R



Battery Models

Equivalent Circuit Model

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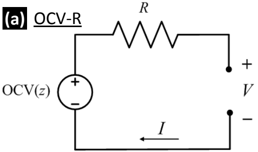
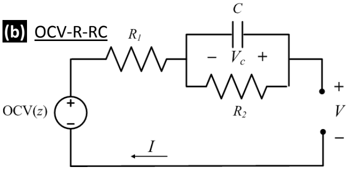
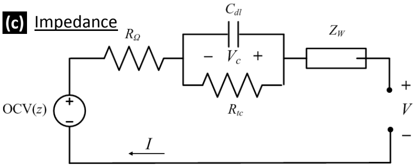


(b) OCV-R-RC



(c) Impedance



Battery Models

Equivalent Circuit Model

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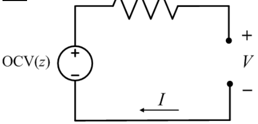

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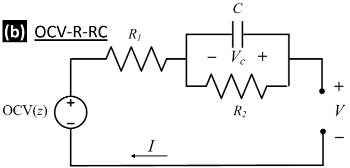

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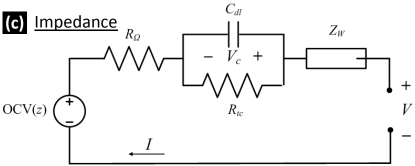
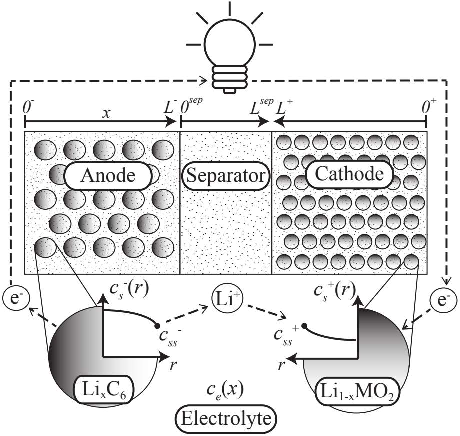
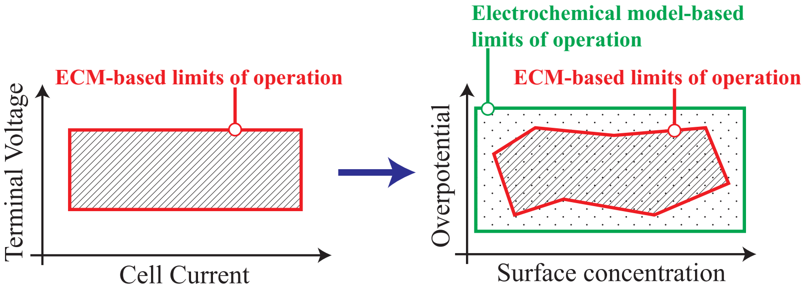


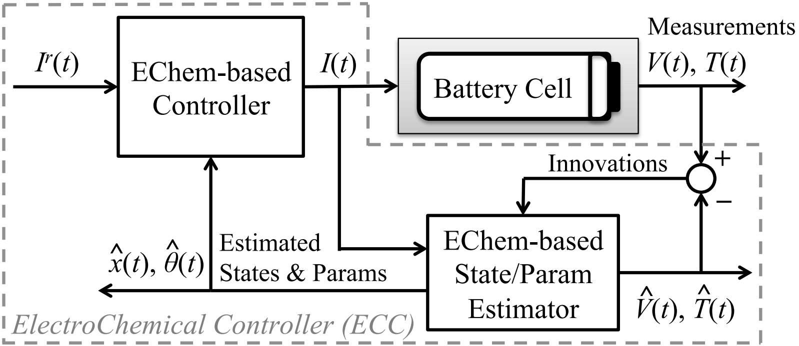
Electrochemical Model

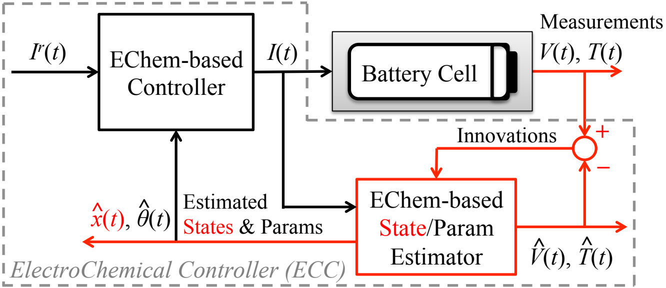


Safely Operate Batteries at their Physical Limits



ElectroChemical Controller (ECC)

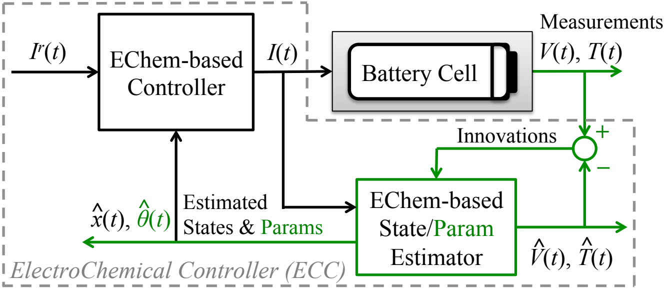




The State (a.k.a. SOC) Estimation Problem

Given measurements of current $I(t)$, voltage $V(t)$, and temperature $T(t)$, estimate the electrochemical states of interest. Exs:

- bulk solid phase Li concentration (state-of-charge)
- surface solid phase Li concentration (state-of-power)

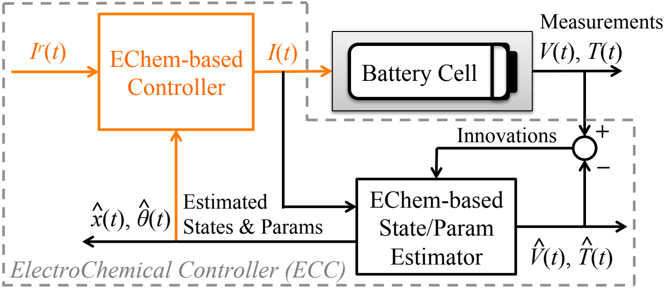


The Parameter (a.k.a. SOH) Estimation Problem

Given measurements of current $I(t)$, voltage $V(t)$, and temperature $T(t)$, estimate uncertain parameters related to SOH. Exs:

- cyclable lithium (capacity fade)
- volume fraction (capacity fade)
- solid-electrolyte interface resistance (power fade)

ElectroChemical Controller (ECC)

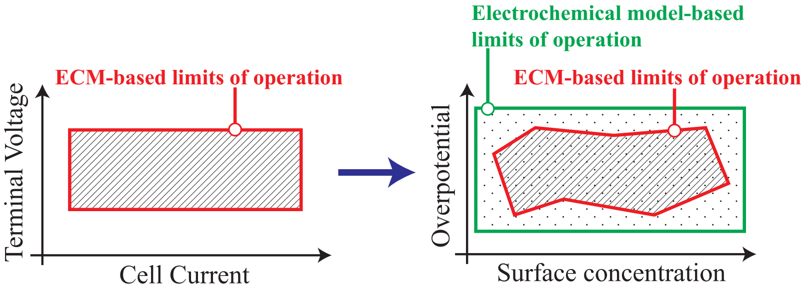


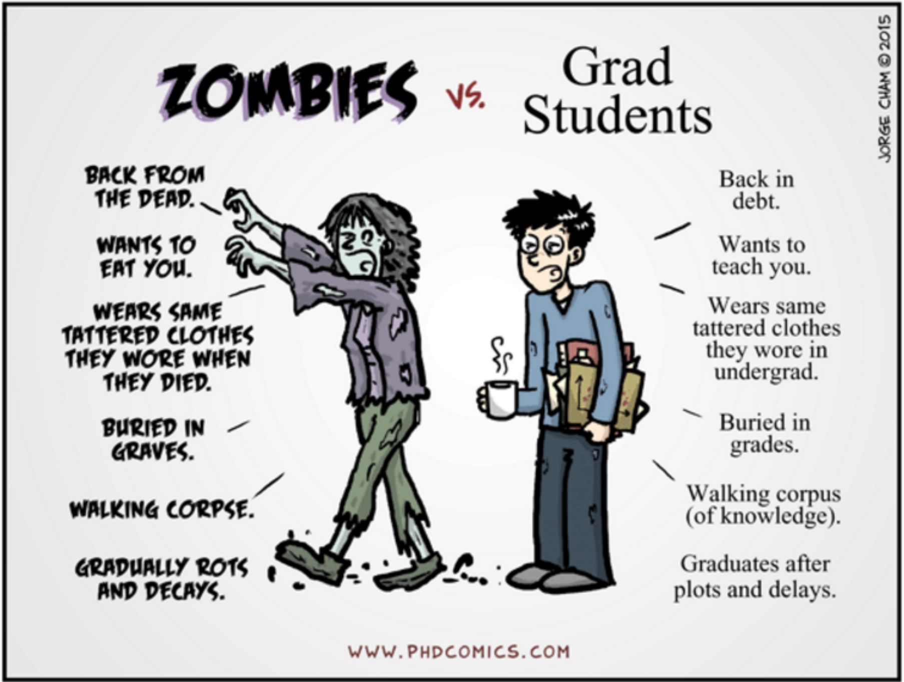
The Constrained Control Problem

Given measurements of current $I(t)$, voltage $V(t)$, and temperature $T(t)$, control current such that critical electrochemical variables are maintained within safe operating constraints. Exs:

- saturation/depletion of solid phase and electrolyte phase
- side-reaction overpotentials
- internal temperature

Safely Operate Batteries at their Physical Limits




ZOMBIES vs. Grad Students
JORGE CHAM © 2015
BACK FROM THE DEAD.
WANTS TO EAT YOU.
WEARS SAME TATTERED CLOTHES THEY WORE WHEN THEY DIED.
BURIED IN GRAVES.
WALKING CORPSE.
GRADUALLY ROTS AND DECAYS.
Back in debt.
Wants to teach you.
Wears same tattered clothes they wore in undergrad.
Buried in grades.
Walking corpus (of knowledge).
Graduates after plots and delays.
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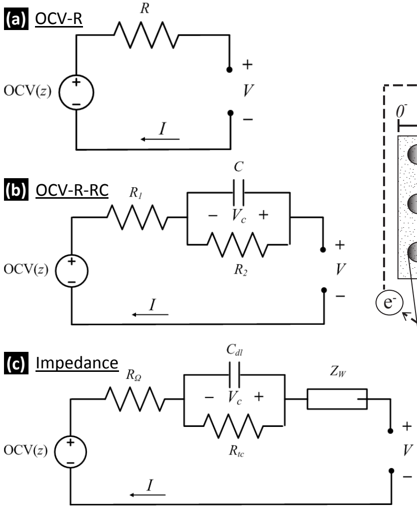
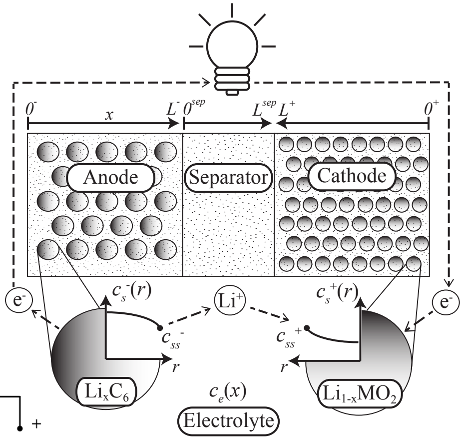
Survey of SOC/SOH Estimation Literature

Equivalent Circuit Model (ECM)



Electrochemical Model



Survey of SOC/SOH Estimation Literature

Equivalent Circuit Model (ECM)

Study ECM variant *X*
with estimation algorithm *Y*

Not the focus here.

Electrochemical Model

EChem-based estimation has recently emerged

Focus on estimation for reduced EChem models

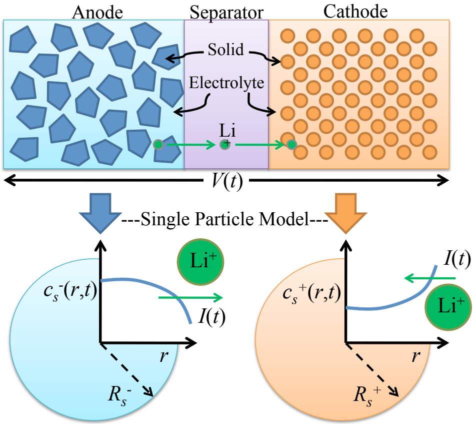
Model reduction and estimation are intimately intertwined

Ideally, want to prove estimation error stability for the highest fidelity model possible

First wave of studies consider a “Single Particle Model” [11], [12], [14], [15]

Difficulty of proving stability increases as model complexity/fidelity increases. Core difficulty is lack of complete observability and nonlinear identifiability.

Single Particle Model (SPM)

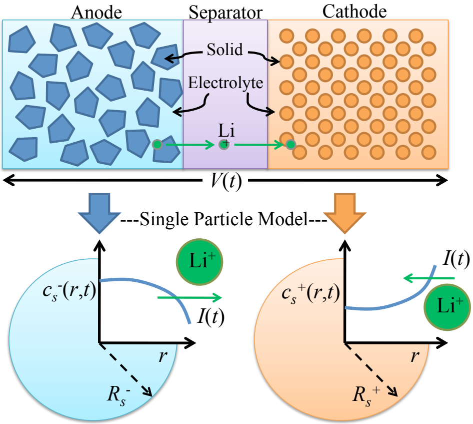


Single Particle Model (SPM)

Diffusion of Li in solid phase:

$$\frac{\partial c_s^-}{\partial t}(r,t) = \frac{D_s^-}{r^2}\frac{\partial}{\partial r}\left[r^2 \frac{\partial^2 c_s^-}{\partial r^2}(r,t)\right]$$

$$\frac{\partial c_s^+}{\partial t}(r,t) = \frac{D_s^+}{r^2}\frac{\partial}{\partial r}\left[r^2 \frac{\partial^2 c_s^+}{\partial r^2}(r,t)\right]$$



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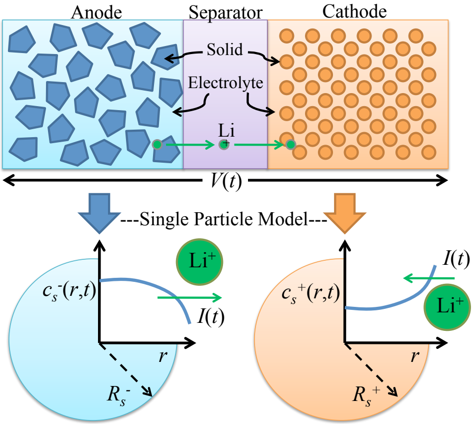
$$\frac{\partial c_s^+}{\partial t}(r,t) = \frac{D_s^+}{r^2}\frac{\partial}{\partial r}\left[r^2 \frac{\partial^2 c_s^+}{\partial r^2}(r,t)\right]$$

Boundary conditions:

$$\frac{\partial c_s^-}{\partial r}(R_s^-,t) = -\rho^- I(t)$$

$$\frac{\partial c_s^+}{\partial r}(R_s^+,t) = \rho^+ I(t)$$



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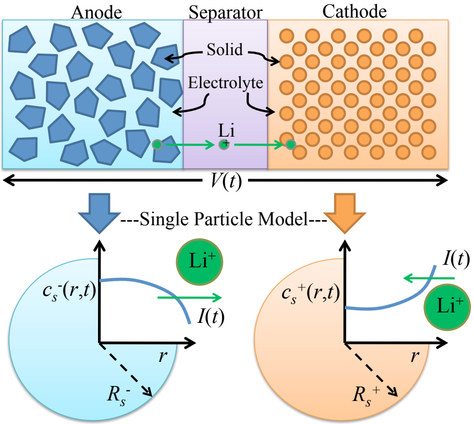
Boundary conditions:

$$\frac{\partial c_s^-}{\partial r}(R_s^-,t) = -\rho^- I(t)$$

$$\frac{\partial c_s^+}{\partial r}(R_s^+,t) = \rho^+ I(t)$$

Voltage Output Function:

$$V(t) = h(c_{ss}^-(t), c_{ss}^+(t), I(t); \theta)$$



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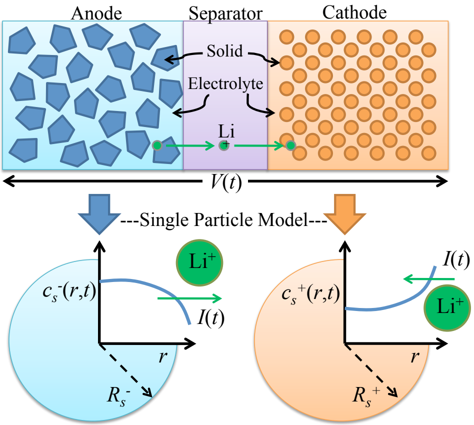
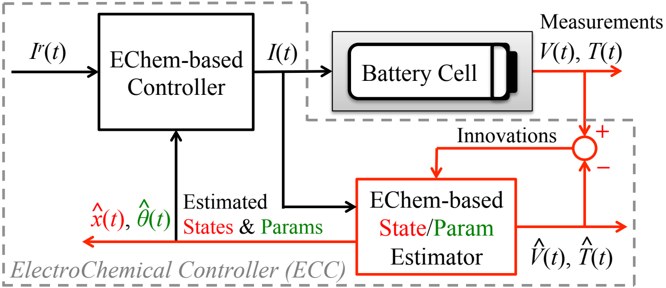


Definitions

- SOC: Bulk concentration SOC_{bulk}, Surface concentration $c_{ss}^-(t)$
- SOH: Physical parameters, e.g. ε, q, n_{Li}, R_f

Adaptive SOC/SOH Problem

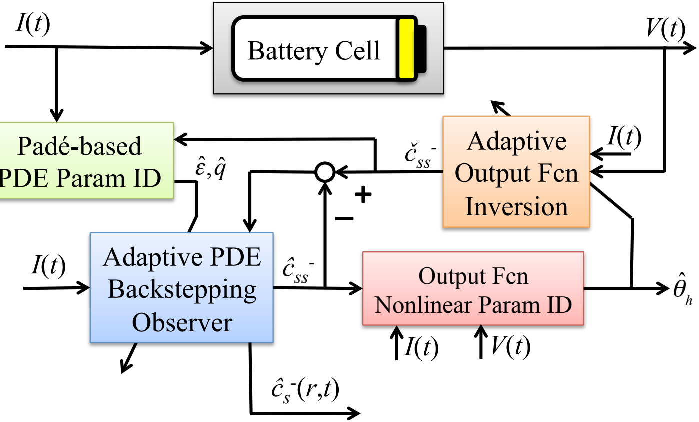


Combined SOC/SOH Problem

Given measurements of current $I(t)$, voltage $V(t)$, and the SPM equations, simultaneously estimate the lithium concentration states $c_s^-(r,t), c_s^+(r,t)$ and parameters θ.

Adaptive Observer

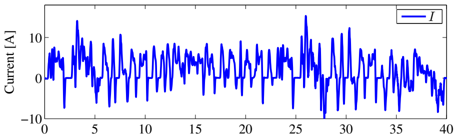
Combined State & Parameter Estimation



S. J. Moura, N. A. Chaturvedi, M. Krstic, "Adaptive PDE Observer for Battery SOC/SOH Estimation via an Electrochemical Model," *ASME Journal of Dynamic Systems, Measurement, and Control*, v 136, n 1, pp. 011015-011026, Oct 2013.

Adaptive Observer Simulations

UDDS Drive Cycle Input



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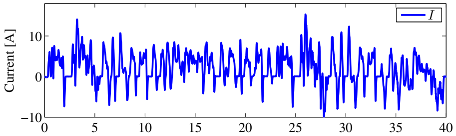

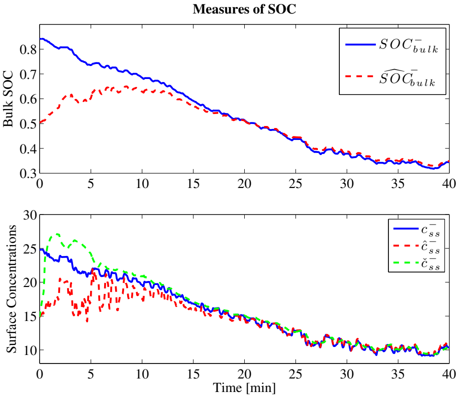

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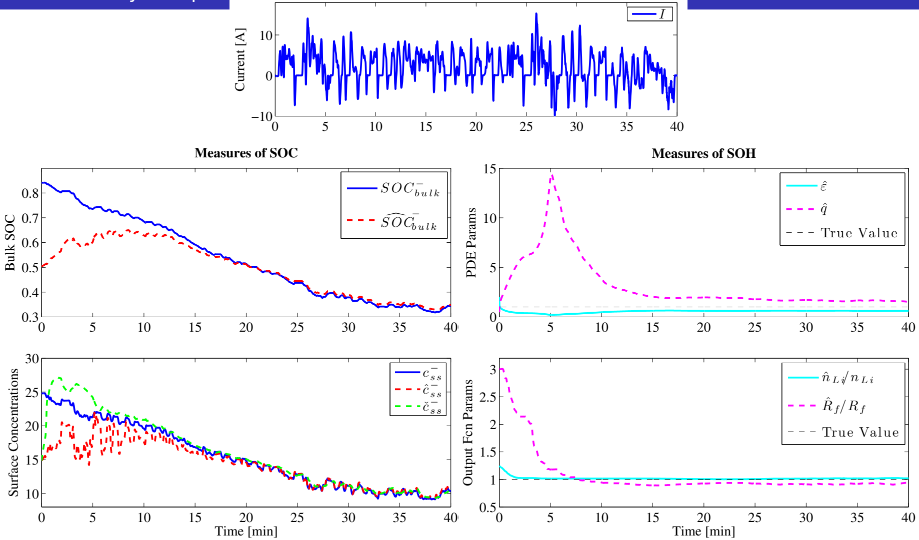

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Operate Batteries at their Physical Limits

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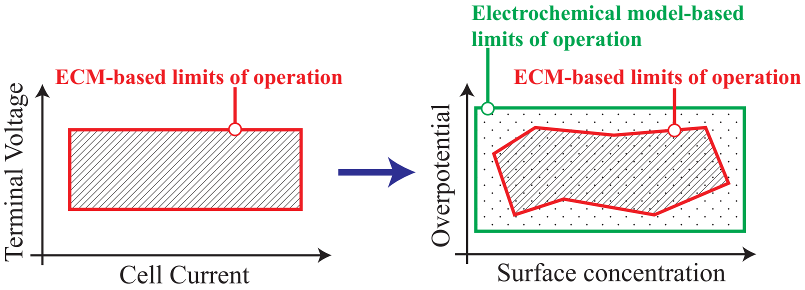

Problem Statement

Given accurate electrochemical state/parameter estimates $(\hat{x}, \hat{\theta})$, govern the input current $I(t)$ such that the EChem constraints are enforced.

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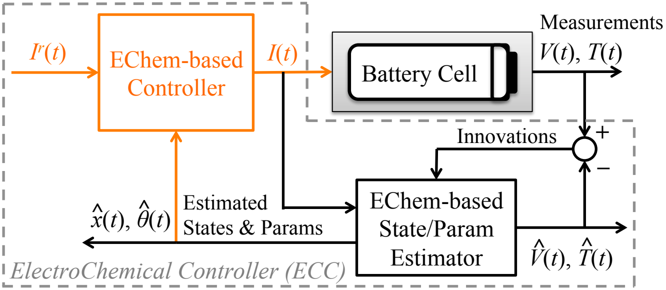


Problem Statement

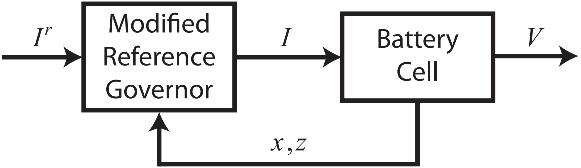
Given accurate electrochemical state/parameter estimates $(\hat{x}, \hat{\theta})$, govern the input current $I(t)$ such that the EChem constraints are enforced.

Constraints

Variable	Definition	Constraint
$I(t)$	Current	Power electronics limits
$c_s^{\pm}(x,r,t)$	Li concentration in solid	Saturation/depletion
$\frac{\partial c_s^{\pm}}{\partial r}(x,r,t)$	Li concentration gradient	Diffusion-induced stress
$c_e(x,t)$	Li concentration in electrolyte	Saturation/depletion
$T(t)$	Temperature	High/low temps accel. aging
$\eta_s(x,t)$	Side-rxn overpotential	Li plating, dendrite formation

Each variable, y, must satisfy $y_{\min} \leq y \leq y_{\max}$.

Modified Reference Governor (MRG)



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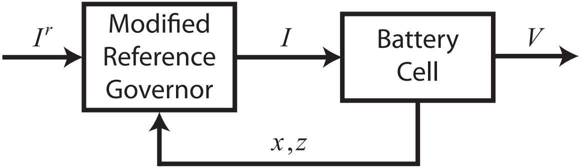

MRG Equations

$$I[k+1] = \beta^*[k] I^r[k], \qquad \beta^* \in [0,1],$$

$$\beta^*[k] = \max\left\{\beta \in [0,1] : (x(t), z(t)) \in \mathcal{O}\right\}$$

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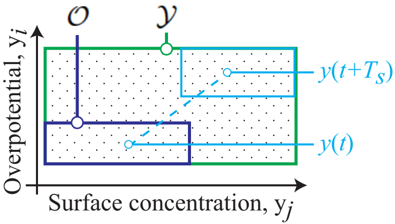

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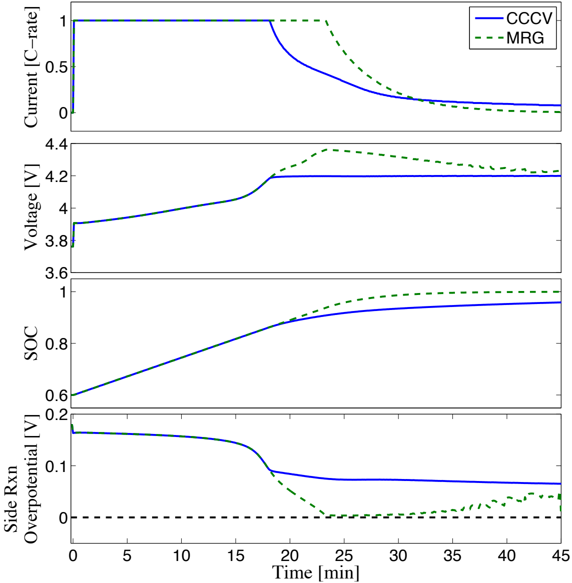
Def'n: Admissible Set $\mathcal{O}$

$$\mathcal{O} = \{(x(t), z(t)) : y(\tau) \in \mathcal{Y}, \forall \tau \in [t, t+T_s]\}$$

$$\begin{aligned} \dot{x}(t) &= f(x(t), z(t), \beta I^r) \\ 0 &= g(x(t), z(t), \beta I^r) \\ y(t) &= C_1 x(t) + C_2 z(t) + D \cdot \beta I^r + E \end{aligned}$$

Application to Charging



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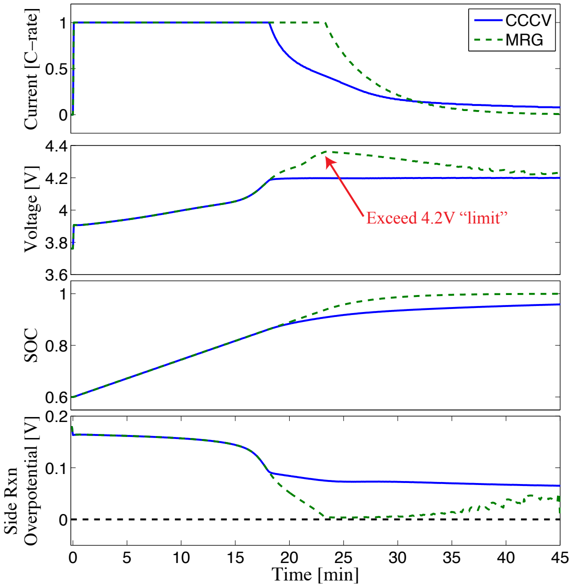

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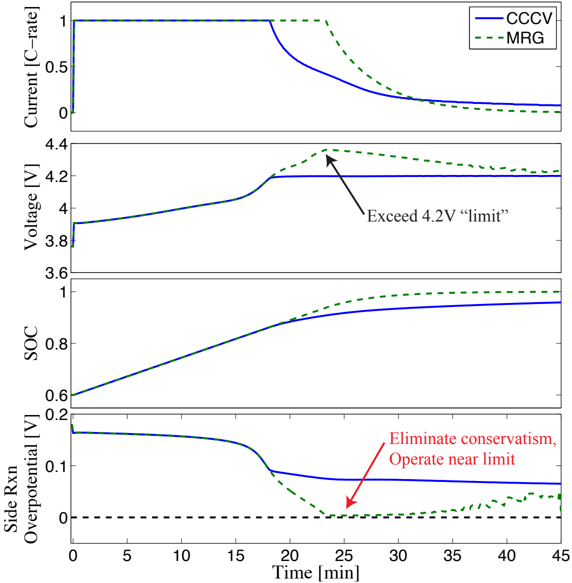

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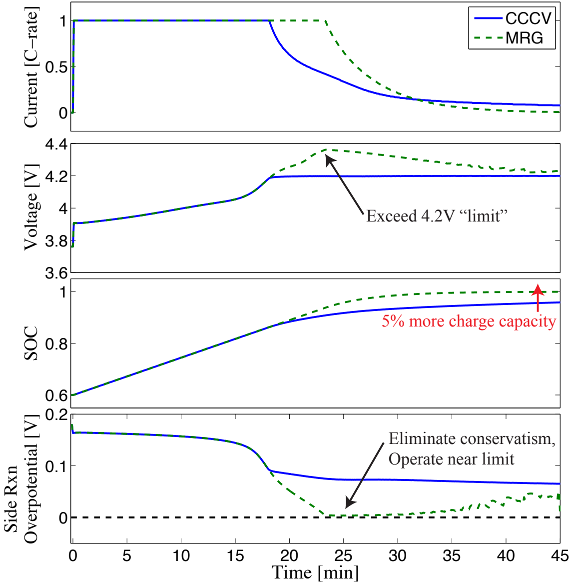
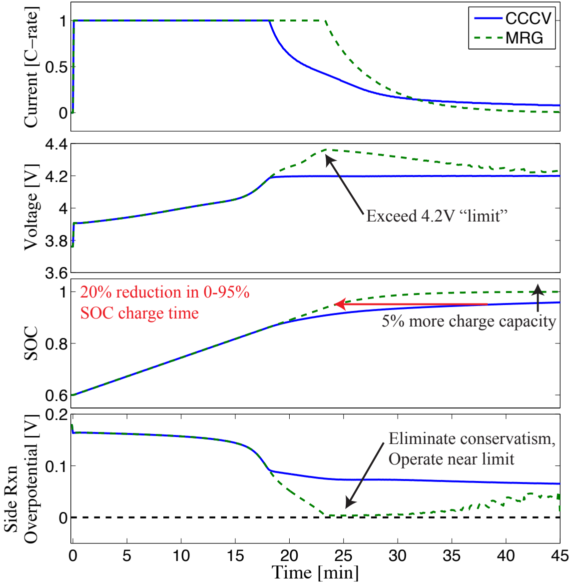


Application to Charging



Fast charge your EV while getting coffee

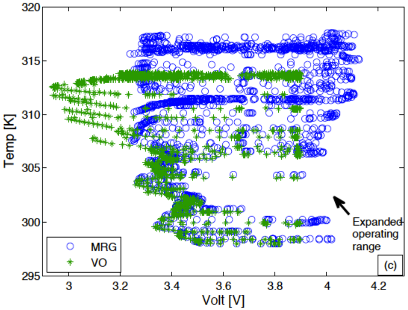
Table: Simulated fast charge times for various C-rates

Charge range	**0.7C** | Traditional	**1.8C** | ECC	**2.5C** | ECC
0-10%	7.92 min	3.17 min	2.33 min
0-20%	17.83 min	7.00 min	5.08 min
0-50%	47.33 min	18.42 min	20.50 min

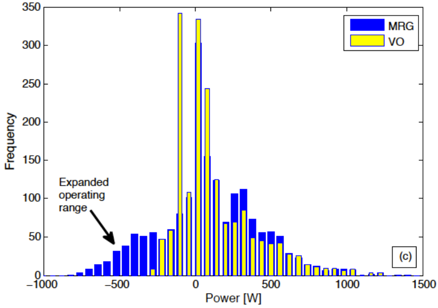
H. E. Perez, N. Shahmohammadhamedani, S. J. Moura, "Enhanced Performance of Li-ion Batteries via Modified Reference Governors & Electrochemical Models," *IEEE/ASME Transactions on Mechatronics*, v 20, n 4, pp. 1511-1520, Aug 2015.

Expanded Operating Range

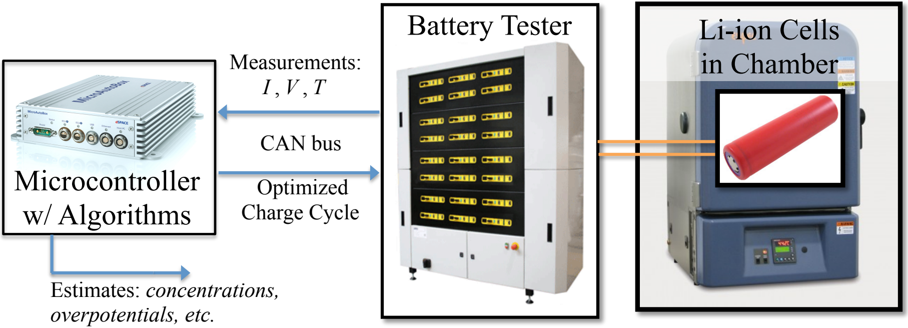
Operating Points on Temperature-Voltage Plane



Power Histogram



Battery-in-the-Loop Test Facility



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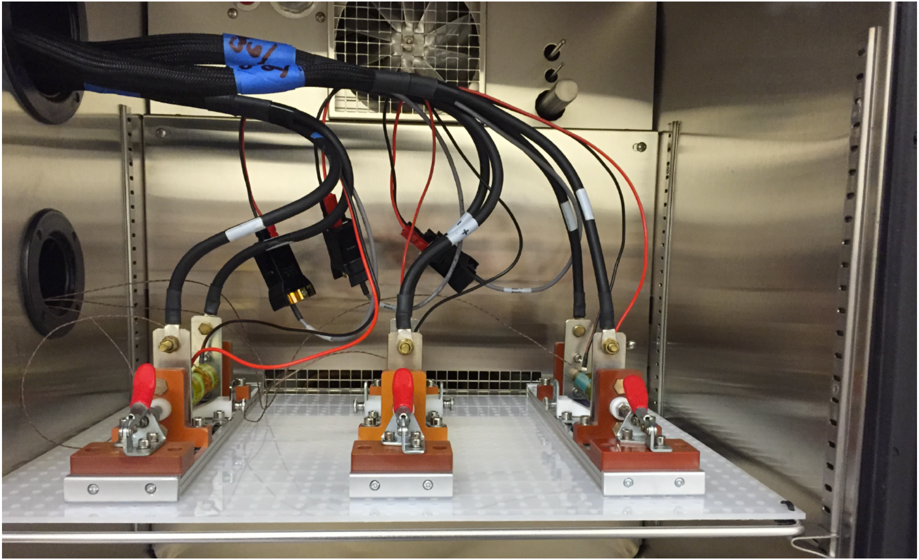

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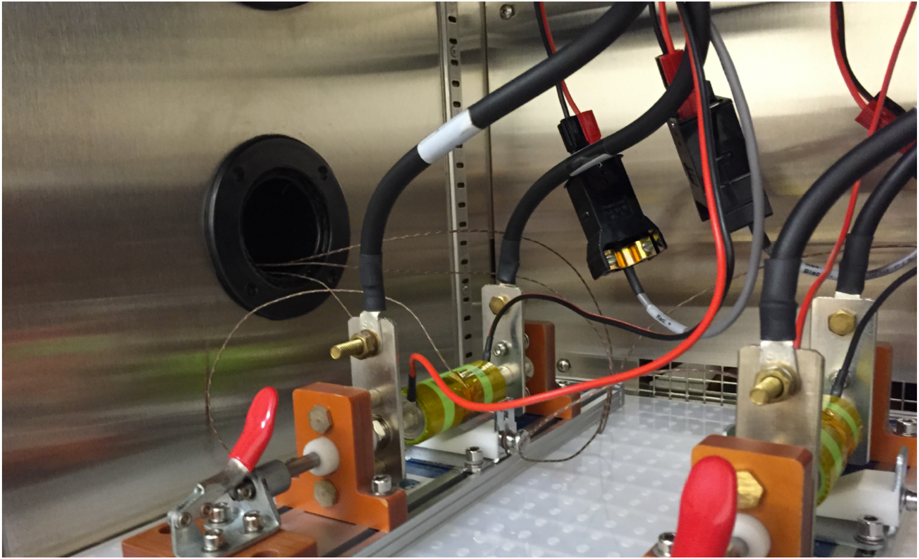

Reading Materials

- S. J. Moura and H. Perez, "Better Batteries through Electrochemistry and Controls," *ASME Dynamic Systems and Control Magazine*, v 2, n 2, pp. S15-S21, July 2014. (Invited Paper).
- N. A. Chaturvedi, R. Klein, J. Christensen, J. Ahmed, and A. Kojic, "Algorithms for advanced battery-management systems," *IEEE Control Systems Magazine*, vol. 30, no. 3, pp. 49-68, 2010.
- H. E. Perez, N. Shahmohammadhamedani, S. J. Moura, "Enhanced Performance of Li-ion Batteries via Modified Reference Governors & Electrochemical Models," *IEEE/ASME Transactions on Mechatronics*, v 20, n 4, pp. 1511-1520, Aug 2015.
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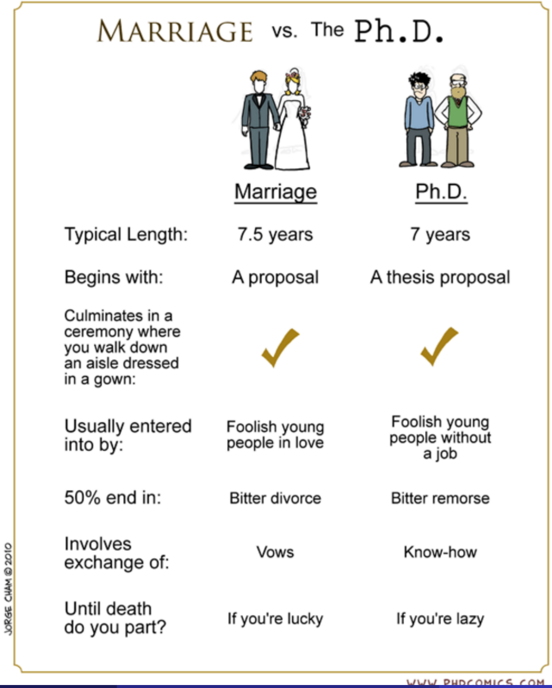
- H. Perez, S. J. Moura, "Sensitivity-Based Interval PDE Observer for Battery SOC Estimation," *2015 American Control Conference*, Chicago, IL, 2015. **Best Student Paper**.
- S. J. Moura, F. Bribiesca Argomedo, R. Klein, A. Mirtabatabaei, M. Krstic, "Battery State Estimation for a Single Particle Model with Electrolyte Dynamics."


MARRIAGE vs. The Ph.D.
Marriage
Ph.D.
Typical Length:
7.5 years
7 years
Begins with:
A proposal
A thesis proposal
Culminates in a ceremony where you walk down an aisle dressed in a gown:
Usually entered into by:
Foolish young people in love
Foolish young people without a job
50% end in:
Bitter divorce
Bitter remorse
Involves exchange of:
Vows
Know-how
Until death do you part?
If you're lucky
If you're lazy
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Outline

1. STORAGE: Electrochemical-based Battery Controls
   - Background & Battery Electrochemistry Fundamentals
   - Estimation and Control Problem Statements
   - State & Parameter Estimation
   - Constrained Optimal Control
2. BUILDINGS: Predictive Energy Management w/ Solar + Storage
   - Forecasting Building Electric Demand
   - Residential Buildings with Solar & Storage
   - Integrating PEV Energy Storage with Buildings
3. GRID: Modeling & Control of Flexible Loads
   - Thermostatically Controlled Loads (TCLS)
   - Plug-in Electric Vehicles (PEVs)

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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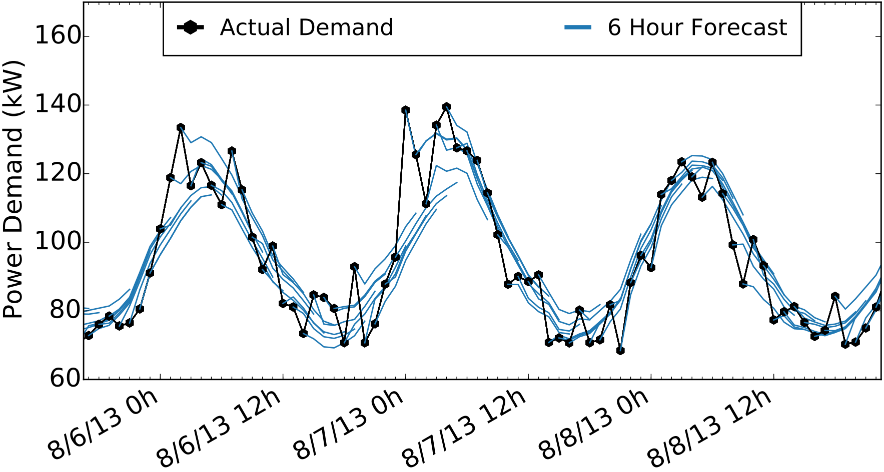
Punchline

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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λ : Weight for regularization penalty

Consider fitting a model of C3 Building 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

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

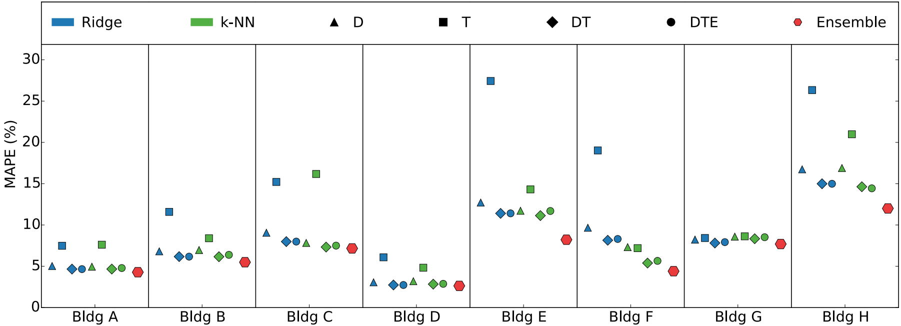
$\theta_{t,s} \in \mathbb{R}$: weights at time-step t, for sub-model s, $\theta_t = [\theta_{t,s}]_{s=1,\cdots,M}$
$y_{t-i} \in \mathbb{R}^m$: observed electricity demand at time step $t-i$
$\hat{y}_{s,t-i} \in \mathbb{R}^m$: predicted electricity demand for sub-model s, at time step $t-i$
$i = 1, \cdots, T$: 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

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



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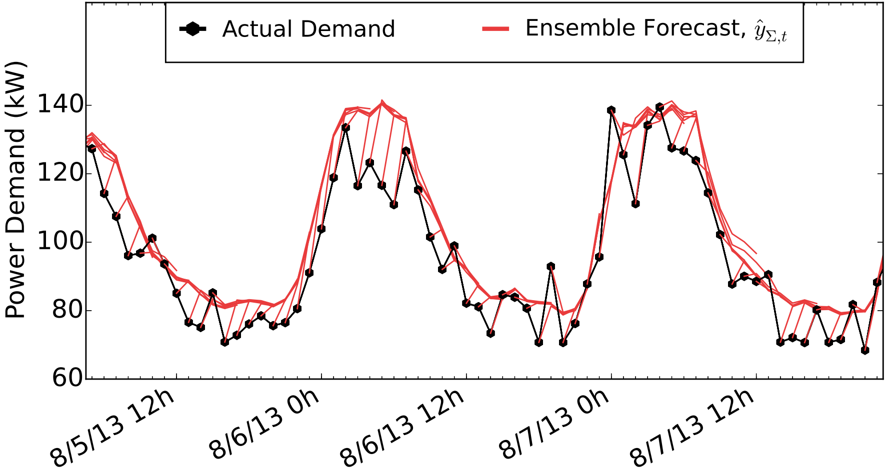
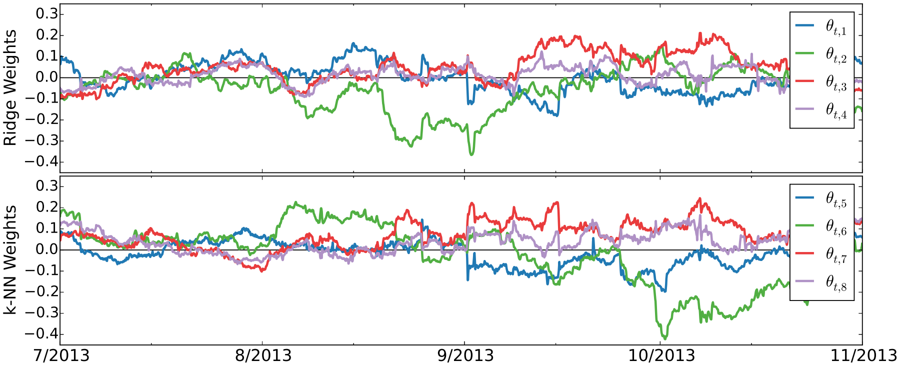
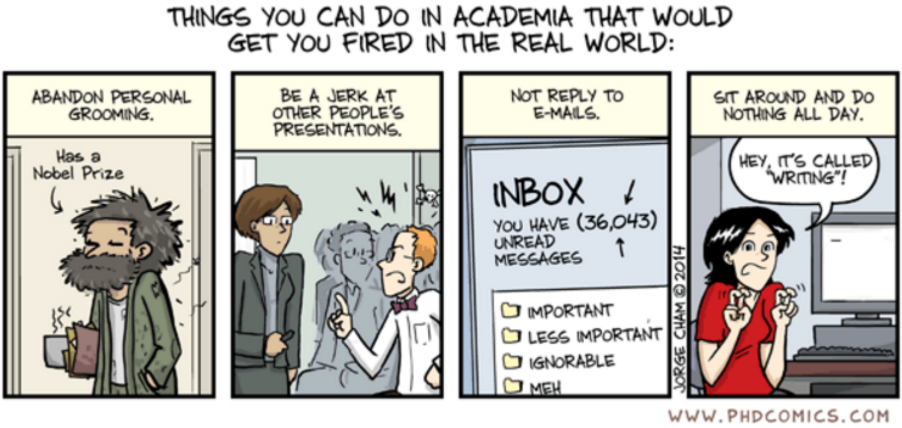
Electricity Demand Forecasting | Dwinelle Offices



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



E. M. Burger, S. J. Moura, “Building Electricity Load Forecasting via Stacking Ensemble Learning Method with Moving Horizon Optimization”. *UC Berkeley: Energy, Controls, and Applications Lab*. Retrieved from: http://escholarship.org/uc/item/6jc7377f


THINGS YOU CAN DO IN ACADEMIA THAT WOULD GET YOU FIRED IN THE REAL WORLD:
ABANDON PERSONAL GROOMING.
Has a Nobel Prize
BE A JERK AT OTHER PEOPLE'S PRESENTATIONS.
NOT REPLY TO E-MAILS.
INBOX
YOU HAVE (36,043) UNREAD MESSAGES
IMPORTANT
LESS IMPORTANT
IGNORABLE
MEH
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SIT AROUND AND DO NOTHING ALL DAY.
HEY, IT'S CALLED "WRITING"!
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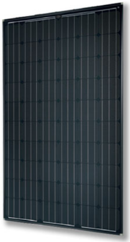
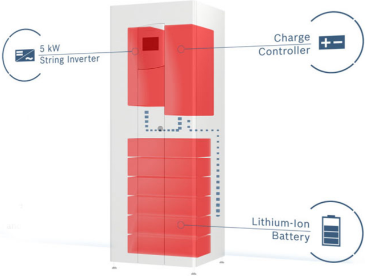
Solar+Storage - An Emergent Market





The Building Solar+Storage Problem

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

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Reality: Current controls are mostly heuristic - no models, no data.

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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
	Photovoltaics/Grid $\leftrightarrow$ Engine
Hybrid Vehicles	Home Demand $\leftrightarrow$ Driver Power Demand
	Battery Storage $\leftrightarrow$ Battery Storage

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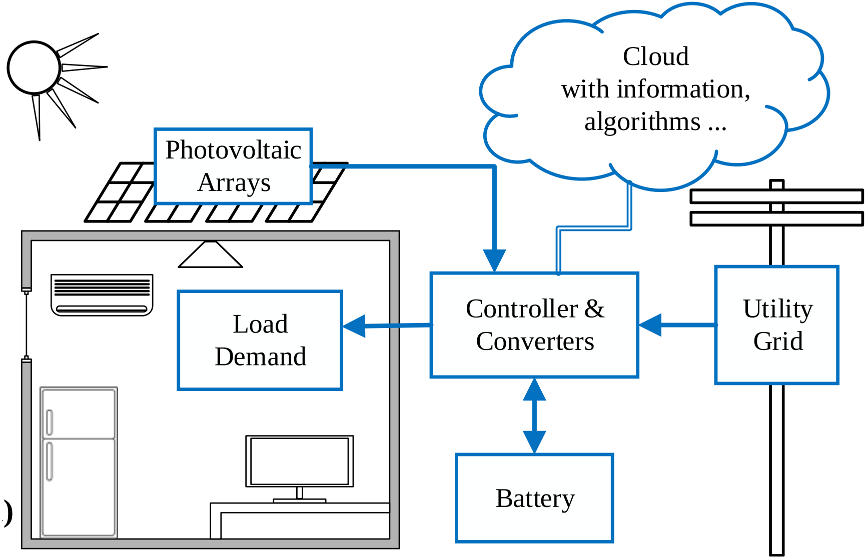
Hybrid Vehicles	Photovoltaics/Grid $\leftrightarrow$ Engine Home Demand $\leftrightarrow$ Driver Power Demand Battery Storage $\leftrightarrow$ Battery Storage

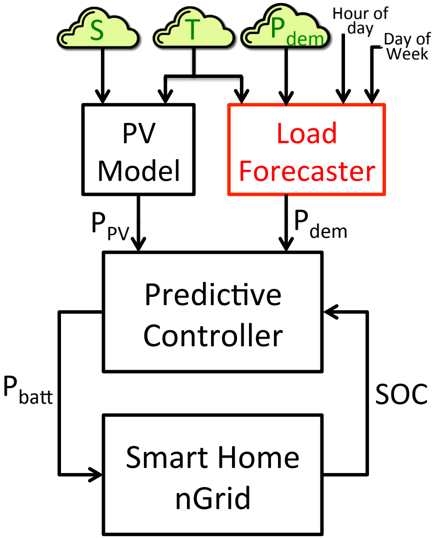
Punchline

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

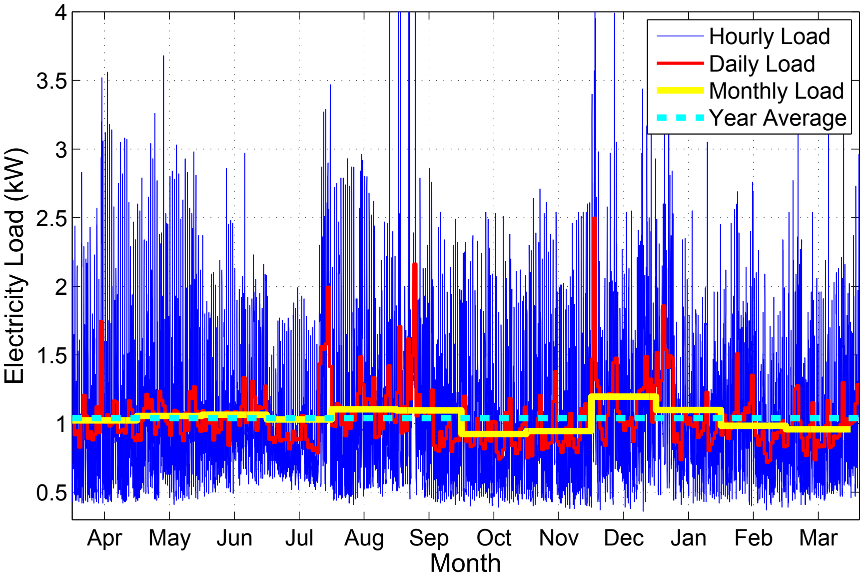
Residential Buildings with Solar & Storage



Predictive Controller with Load/Weather Forecasting



Single-Family Home Energy Patterns in LA



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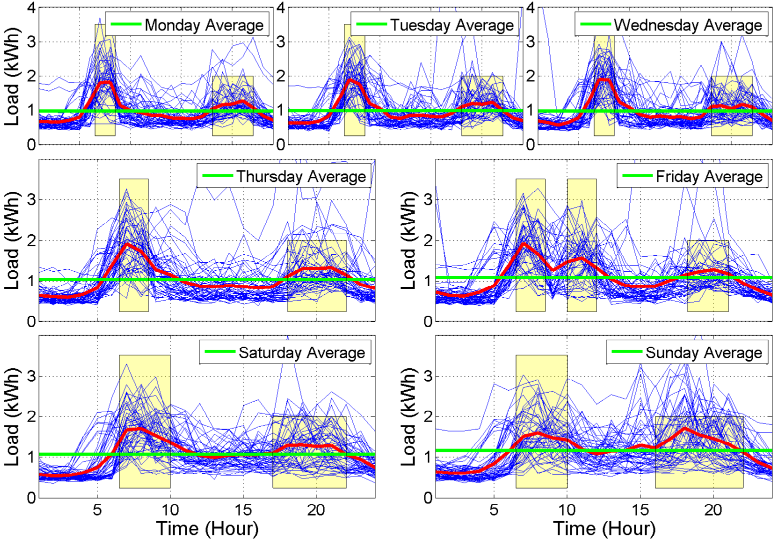

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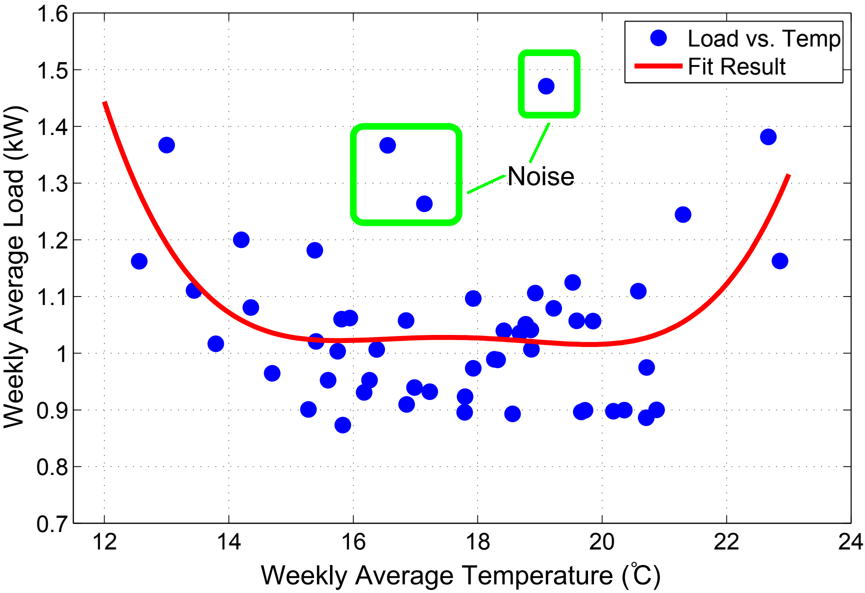
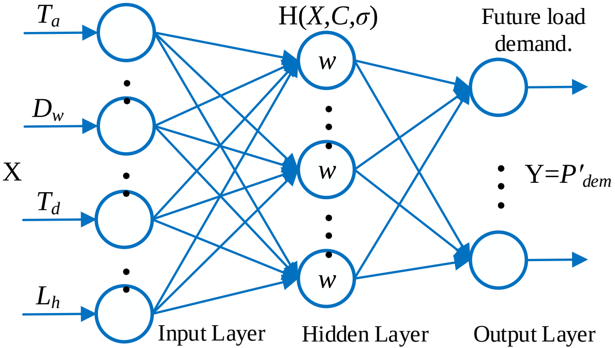


Artificial Neural Network (ANN)

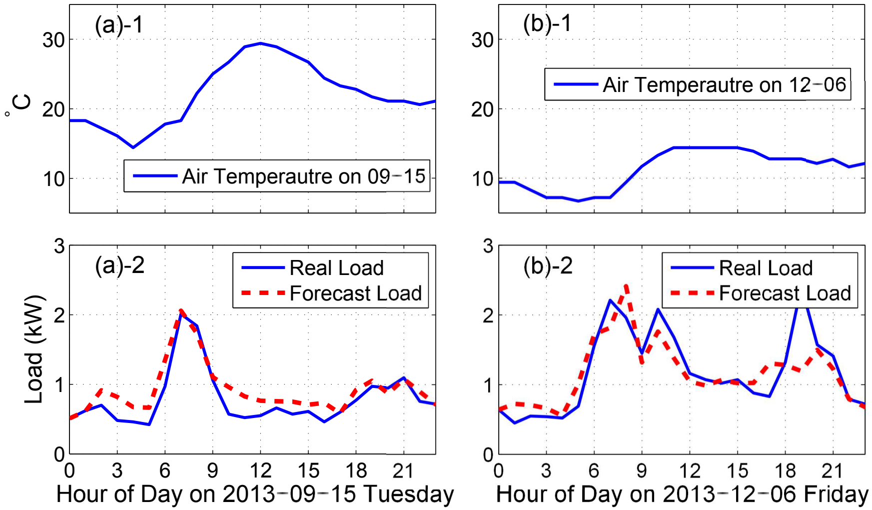


$$Y = f_{ANN}(X), \quad X = [T_a, D_w, T_d, L_h], \quad Y = [P_{dem,k+1}, \cdots, P_{dem,k+m}]$$

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

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

Short-term Forecast of Home Load



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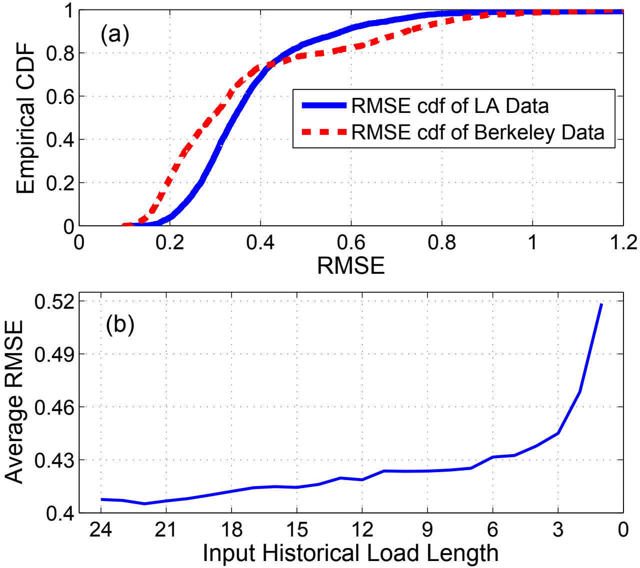
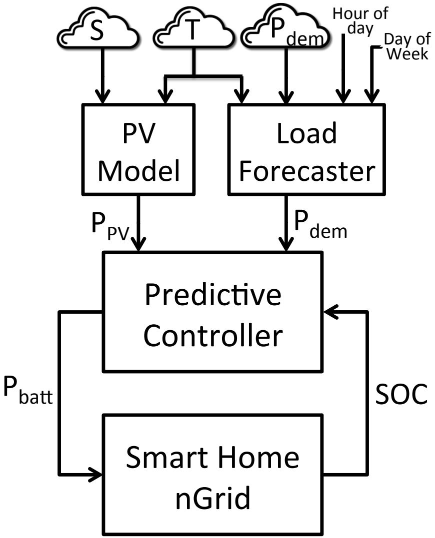


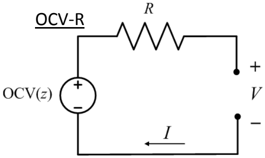
Cloud-Enabled Control



Battery and Photovoltaic Cell Models

battery

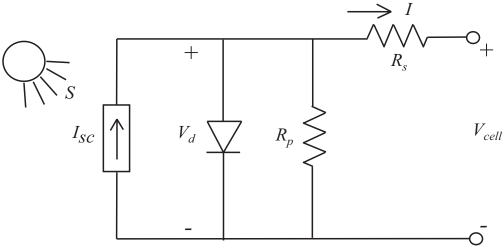
$$\frac{d}{dt} SOC(t) = -\frac{I_{batt}(t)}{Q},$$
$$P_{batt}(t) = V_{oc} I_{batt}(t) - I_{batt}^2(t) R_{in},$$



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.

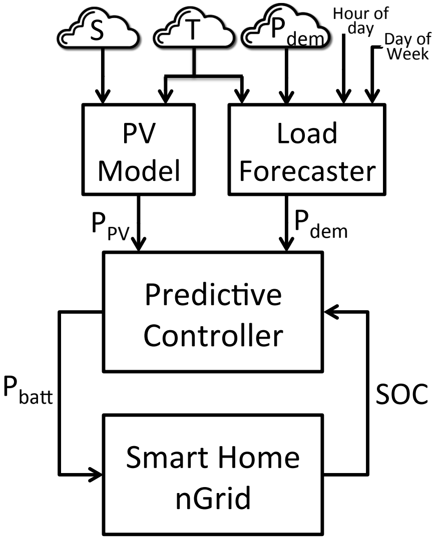
photovoltaics

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

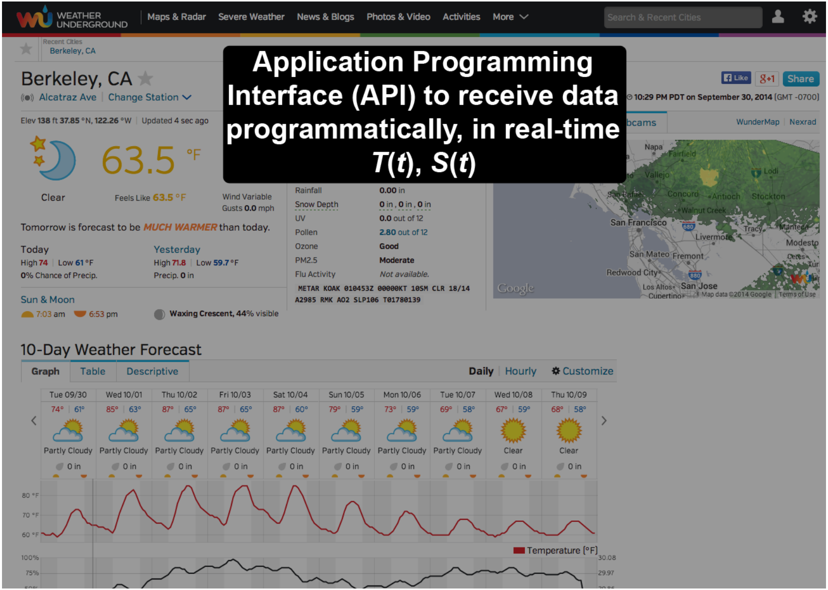


G. Vachtsevanos and K. Kalaitzakis, "A hybrid photovoltaic simulator for utility interactive studies," *IEEE Transactions on Energy Conversion*, no. 2, pp. 227-231, 1987.

Internet-based Data Feeds



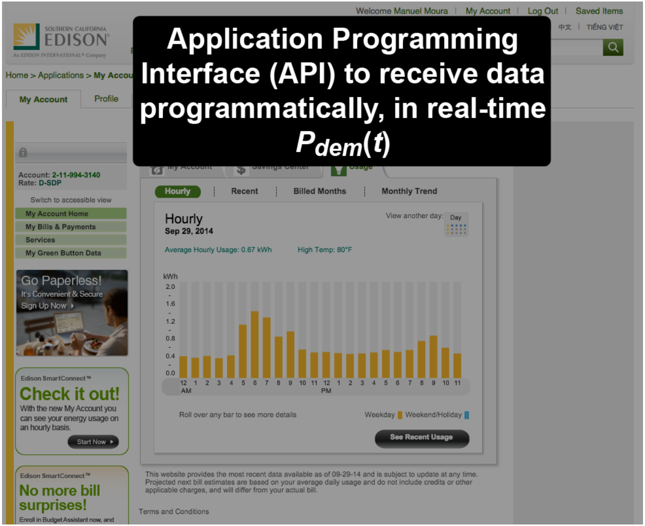
Internet-based Data Feeds



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

***T*(*t*), *S*(*t*)**

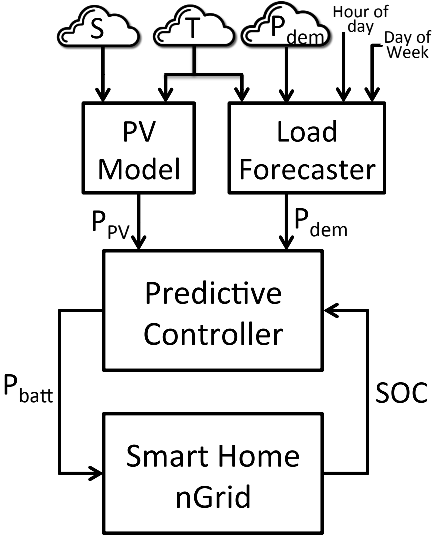
Internet-based Data Feeds



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

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

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

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

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

$$P_{batt}^{\min} \leq P_{batt} \leq P_{batt}^{\max}, \; P_{grid}^{\min} \leq P_{grid} \leq P_{grid}^{\max},$$

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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$$P_{batt}^{\text{min}} \leq P_{batt} \leq P_{batt}^{\text{max}}, \; P_{grid}^{\text{min}} \leq P_{grid} \leq P_{grid}^{\text{max}},$$

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

Nonlinear MPC Formulation

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

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

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

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$$P_{batt}^{\mathrm{min}} \leq P_{batt} \leq P_{batt}^{\mathrm{max}}, \; P_{grid}^{\mathrm{min}} \leq P_{grid} \leq P_{grid}^{\mathrm{max}},$$

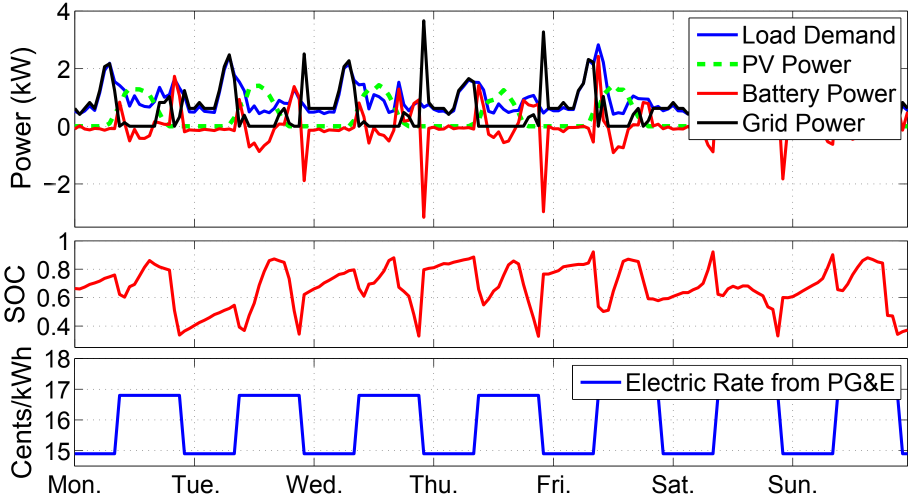
$$\hat{d}\left((k+n)\Delta t\right) = f_{forecast}(d(k\Delta t), \cdots, d((k-H_h)\Delta t)), \quad n = 1, \cdots, H_p$$

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

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

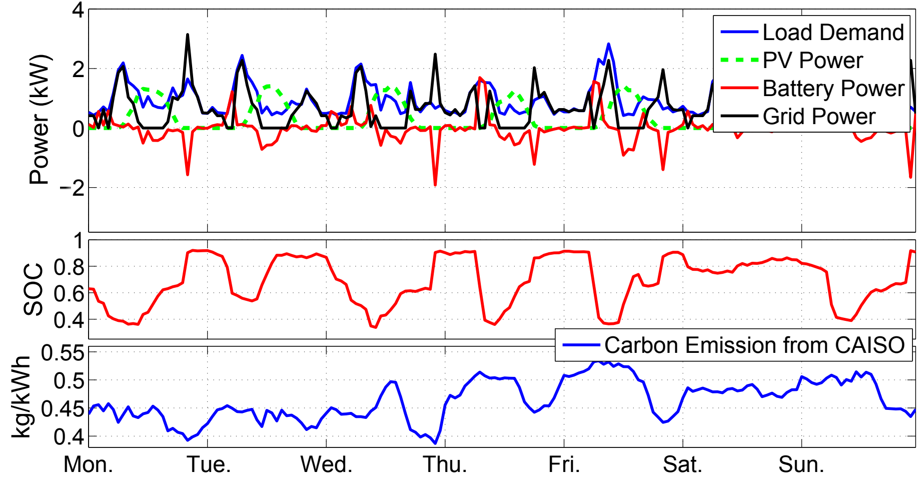
Solved via Dynamic Programming

Model Predictive Control w/ Cloud-enabled Forecasts



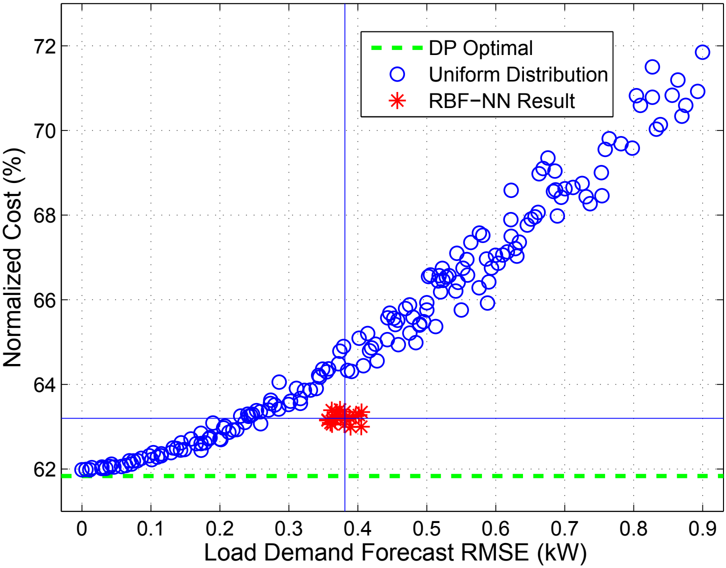
Optimize for Grid Electricity Cost

Model Predictive Control w/ Cloud-enabled Forecasts



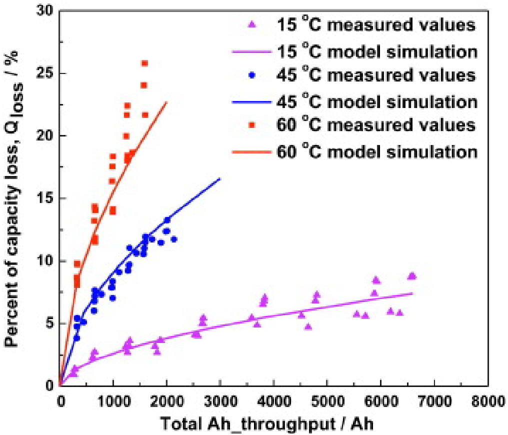
Optimize for Marginal CO_2 Produced from Power Plants

Load Forecasting - how accurate is accurate enough?

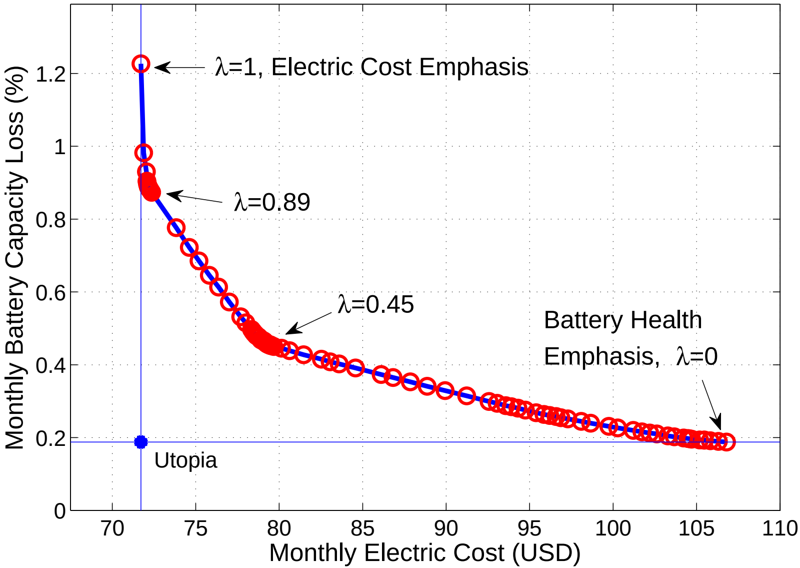


Battery Health Aware

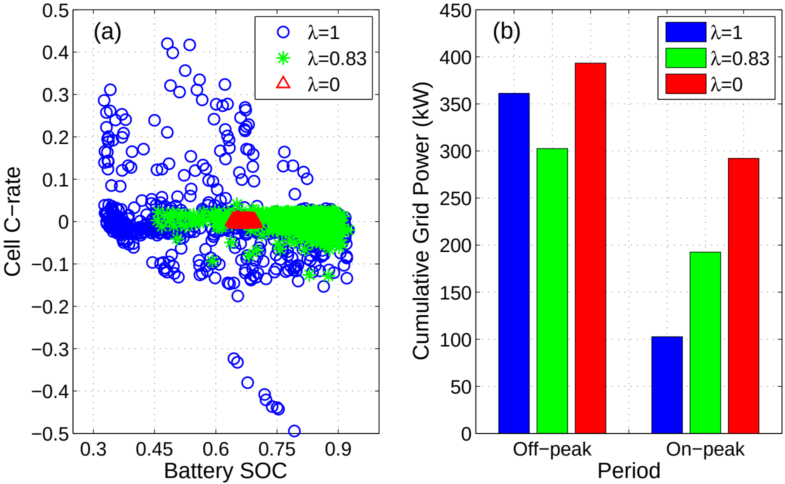
$$\min \qquad J_k = \int_{k\Delta t}^{(k+H_p)\Delta t} \left[\lambda \cdot ElecPrice(u,t) + (1-\lambda)\cdot Q_{loss}(u)\right]^2 \, dt$$



Battery Health Aware



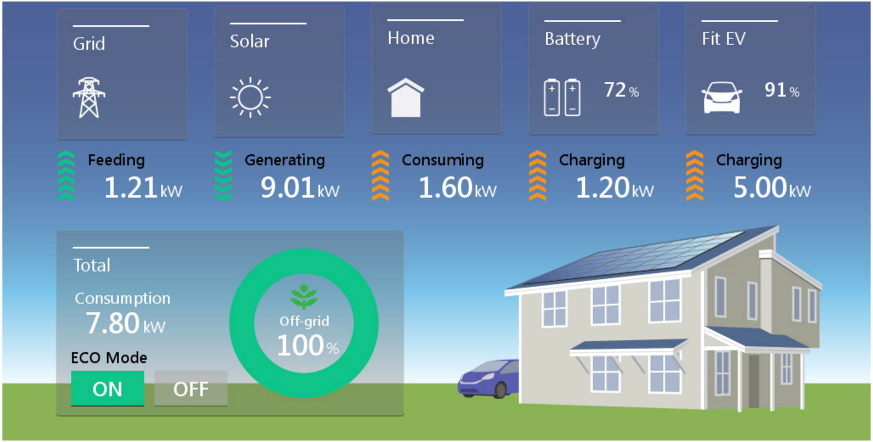
Battery Health Aware



C. Sun, F. Sun, S. J. Moura, "Nonlinear Predictive Energy Management of Residential Buildings with Photovoltaics & Batteries". *UC Berkeley: Energy, Controls, and Applications Lab*. Retrieved from: http://escholarship.org/uc/item/1897t9cg

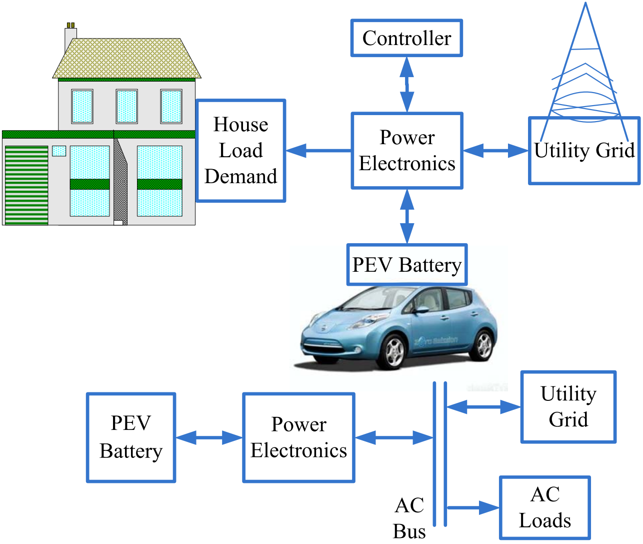
Smart Home Demonstration Project @ UC Davis

Smart Home Demonstration Project @ UC Davis



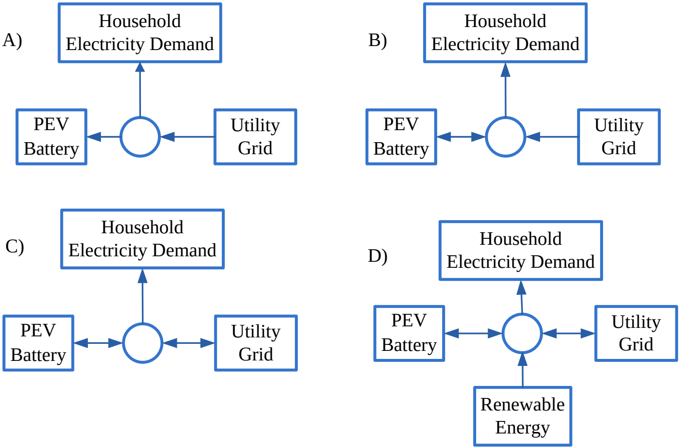

I'D LIKE TO INTRODUCE YOU TO BETH, AN ANTHROPOLOGY P.H.D. STUDENT.
HI, HOW IS YOUR RESEARCH GOING?
SMACK!
WHAT'S THE MATTER WITH YOU?
WHY I NEVER...
DON'T YOU KNOW IT'S BAD MANNERS TO ASK A P.H.D. STUDENT THAT?
I-I'M SORRY. UH, SO... HOW LONG BEFORE YOU FINISH YOUR THESIS?
SMACK!
GEEZ, WHY DON'T YOU ASK HER FOR HER WEIGHT OR HER AGE WHILE YOU'RE AT IT?
THANKS TO MIGUEL...
JORGE CHAM ©THE STANFORD DAILY

Stochastic PEV Energy Storage



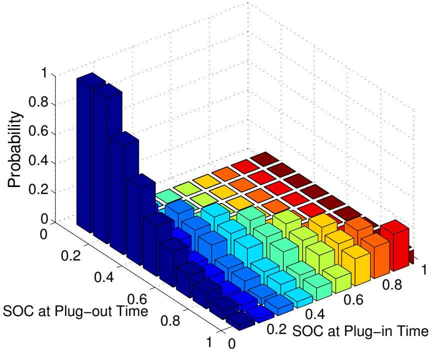
X. Wu, X. Hu, X. Yin, S. J. Moura, “Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage” *in review*.

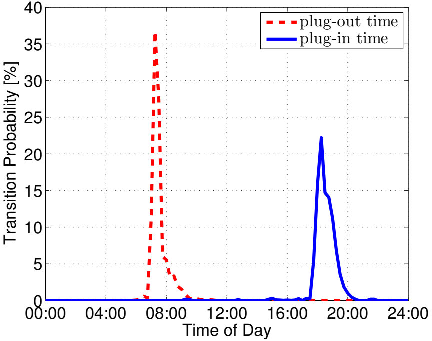
PEV-Home Nanogrid Operating Modes



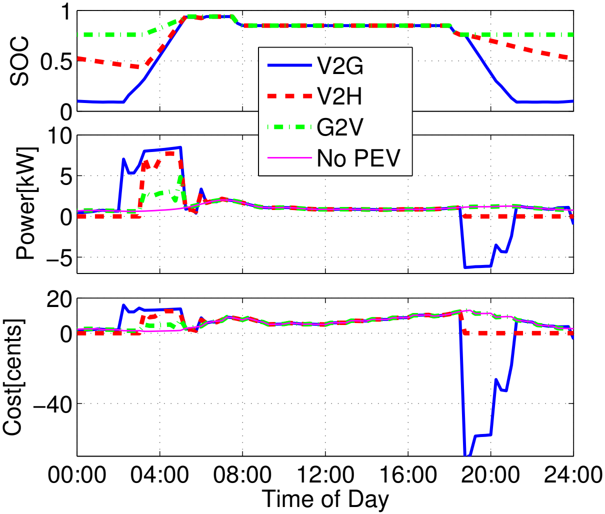
A) Grid-to-Vehicle (G2V); B) Vehicle-to-Home (V2H); C) Vehicle-to-Grid (V2G); D) V2G w/ PV

Stochastic Mobility Needs





Stochastic Dynamic Programming Results



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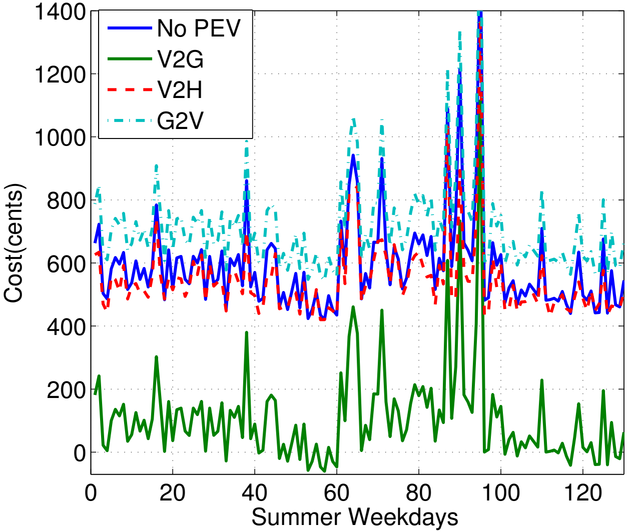
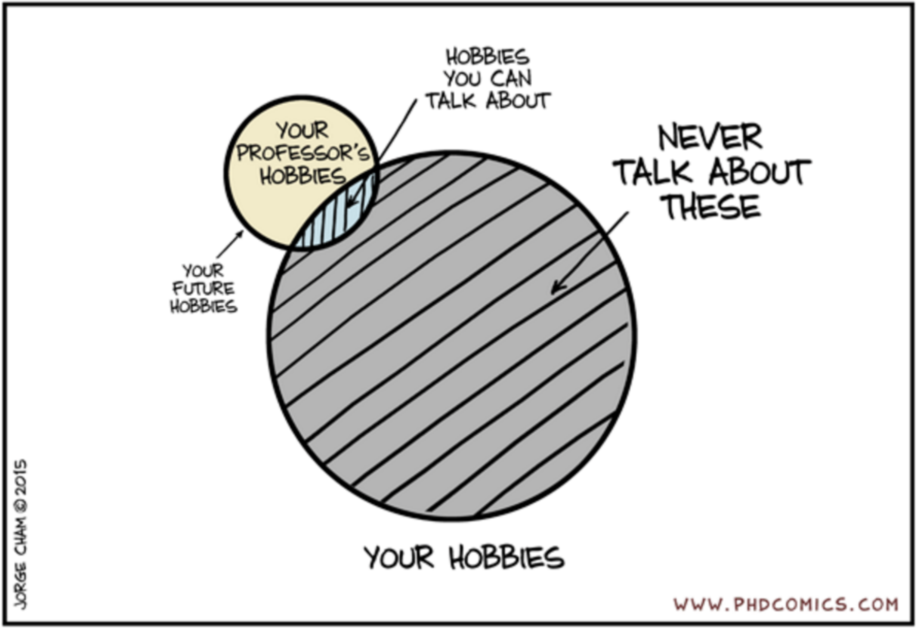
Stochastic Dynamic Programming Results



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

Reading Materials

- E. Burger, S. J. Moura, "Gated Ensemble Learning Method for Demand-Side Electricity Load Forecasting," *Energy and Buildings*, v 109, pp. 23-34, Dec 2015.
- E. M. Burger, S. J. Moura, "Building Electricity Load Forecasting via Stacking Ensemble Learning Method with Moving Horizon Optimization". *UC Berkeley: Energy, Controls, and Applications Lab*. Retrieved from: http://escholarship.org/uc/item/6jc7377f
- C. Sun, F. Sun, S. J. Moura, "Nonlinear Predictive Energy Management of Residential Buildings with Photovoltaics & Batteries". *UC Berkeley: Energy, Controls, and Applications Lab*. Retrieved from: http://escholarship.org/uc/item/1897t9cg
- X. Wu, X. Hu, X. Yin, S. J. Moura, "Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage" *in review*.


HOBBIES YOU CAN TALK ABOUT
YOUR PROFESSOR'S HOBBIES
NEVER TALK ABOUT THESE
YOUR FUTURE HOBBIES
YOUR HOBBIES
JORGE CHAM © 2015
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Outline

1. STORAGE: Electrochemical-based Battery Controls
   - Background & Battery Electrochemistry Fundamentals
   - Estimation and Control Problem Statements
   - State & Parameter Estimation
   - Constrained Optimal Control
2. BUILDINGS: Predictive Energy Management w/ Solar + Storage
   - Forecasting Building Electric Demand
   - Residential Buildings with Solar & Storage
   - Integrating PEV Energy Storage with Buildings
3. GRID: Modeling & Control of Flexible Loads
   - Thermostatically Controlled Loads (TCLS)
   - Plug-in Electric Vehicles (PEVs)

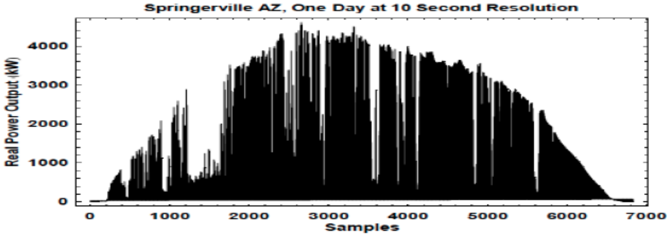
Renewables: Where and How much?

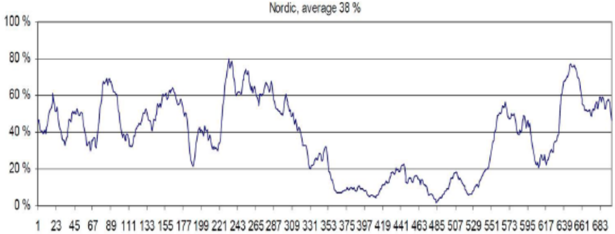
Grid-Side



Distribution-Side


Variability is the Issue!





Solar data – Jay Apt and Aimee Curtright, CMU, 2009

Wind data – Hourly power from Nordic grid for Feb. 2000 P. Norgard et al.,2004 Sou

Integration Costs

- Increased variability is *the* problem!
  - Operation Challenges: $\pm$3 GW/h wind ramps
  - Reserve Requirements: 3X increases needed
- Reserve capacity increases needed with current practice under 33% penetration in CA [Helman 2010]
  - Load Following: 2.3 GW $\rightarrow$ 4.4 GW
  - Regulation: 227 MW $\rightarrow$ 1.4 GW
  - Excess reserves defeat carbon benefits
- Added costs due to reserves at 15% renewable penetration
  - $\approx$ 2.50 - 5 USD per MW of renewable generation EWITS study, NREL 2010

Reserves are a significant cost for renewable integration

Mitigating Reserve Costs

Supply-side	Improved forecasting
Better use of Information	Risk limiting dispatch
Demand-side	"Smart" Flexible Devices
Exploiting flexibility	Electric vehicles, HVACs, Water heaters, etc.

The Demand-Side Management Problem

Needs: Integrate renewables AND enhance resilience/sustainability

Obstacle: Control populations of loads - stochastic, distributed, constrained

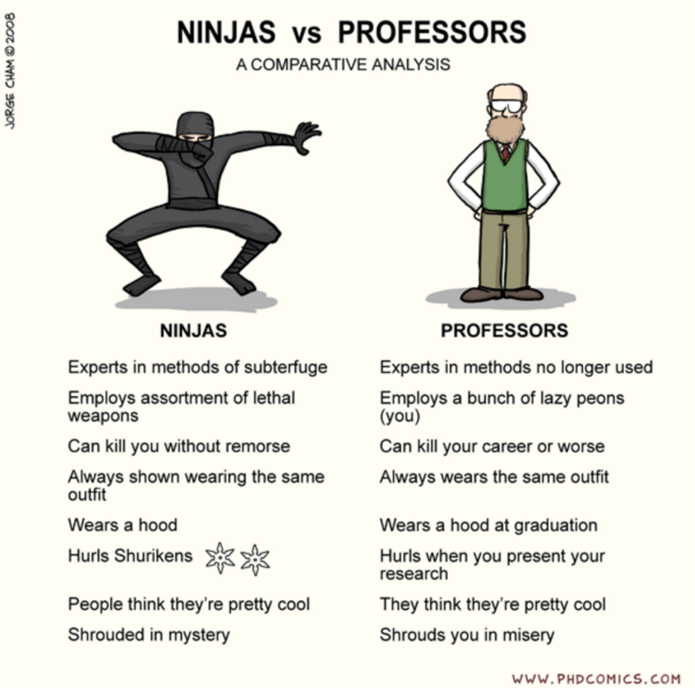
Definition (Flexible Loads):
Devices with controllable load profiles,
e.g. Electric vehicles, HVAC, electric water heaters, refrigerators

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 for power system reserves


JORGE CHAM © 2008
NINJAS vs PROFESSORS
A COMPARATIVE ANALYSIS
NINJAS
PROFESSORS
Experts in methods of subterfuge
Experts in methods no longer used
Employs assortment of lethal weapons
Employs a bunch of lazy peons (you)
Can kill you without remorse
Can kill your career or worse
Always shown wearing the same outfit
Always wears the same outfit
Wears a hood
Wears a hood at graduation
Hurls Shurikens
Hurls when you present your research
People think they're pretty cool
They think they're pretty cool
Shrouded in mystery
Shrouds you in misery
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Modeling Aggregated TCLs

Main Idea: Convert $> 10^3$ ODEs into two coupled linear PDEs

Modeling Aggregated TCLs

Main Idea: Convert $> 10^3$ ODEs into two coupled linear PDEs

$$\begin{array}{c|l} u(T,t) & \text{\# TCLs / }^\circ\text{C, in COOL state, @ temp } T\text{, time } t \\ v(T,t) & \text{\# TCLs / }^\circ\text{C, in HEAT state, @ temp } T\text{, time } t \end{array}$$

Modeling Aggregated TCLs

Main Idea: Convert $> 10^3$ ODEs into two coupled linear PDEs

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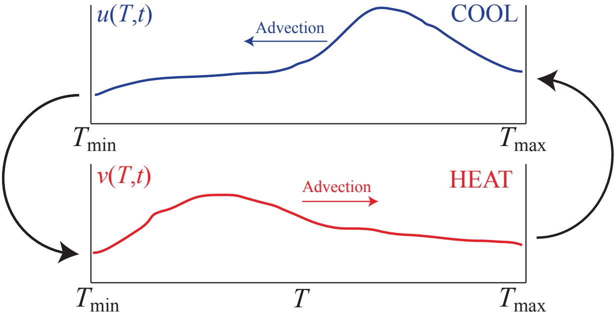

Modeling Aggregated TCLs

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$u(T,t)$	# TCLs / °C, in COOL state, @ temp T, time t
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Flux of TCLs in HEAT state:
#TCLs / sec

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

Modeling Aggregated TCLs

Main Idea: Convert $> 10^3$ ODEs into two coupled linear PDEs

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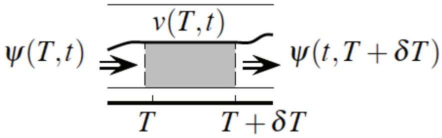
Control volume:



Modeling Aggregated TCLs

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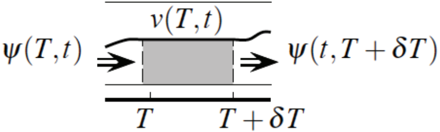
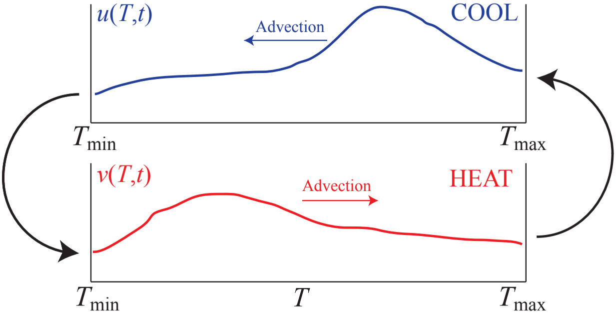
Control volume:

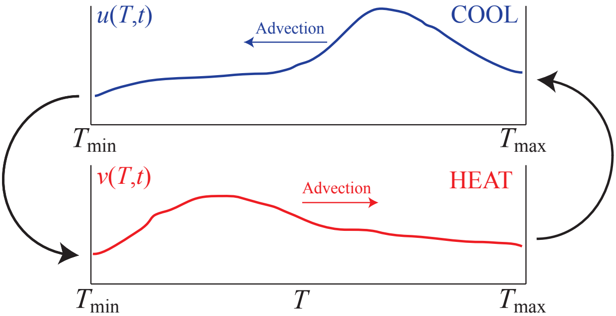


$$\begin{aligned} \frac{\partial v}{\partial t}(T,t) &= \lim_{\delta T \to 0}\left[\frac{\psi(T+\delta T,t) - \psi(T,t)}{\delta T}\right] \\ &= \frac{\partial \psi}{\partial T}(T,t) \\ &= -\frac{1}{RC}\left[T_\infty - T(t)\right]\frac{\partial v}{\partial T}(T,t) + \frac{1}{RC}v(T,t) \end{aligned}$$

PDE Model of Aggregated TCLs



PDE Model of Aggregated TCLs



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

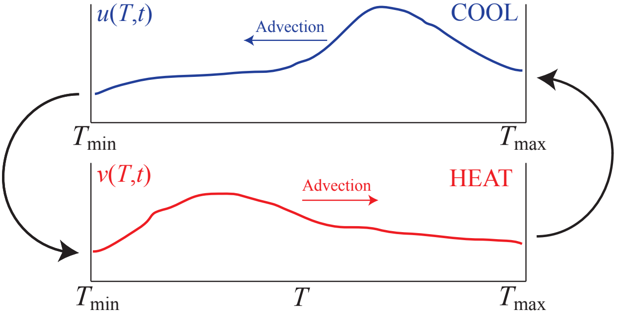
$$v_t(T,t) = -\alpha\mu(T)v_T(T,t) + \alpha v(T,t)$$

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

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

Video of 1,000 TCLs

PDE Model of Aggregated TCLs



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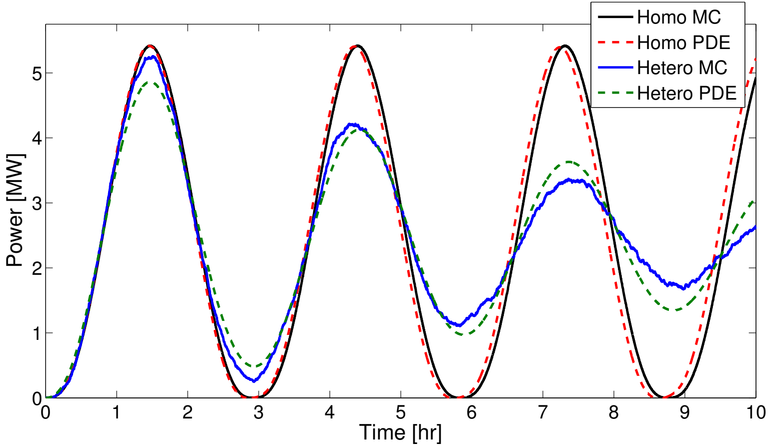
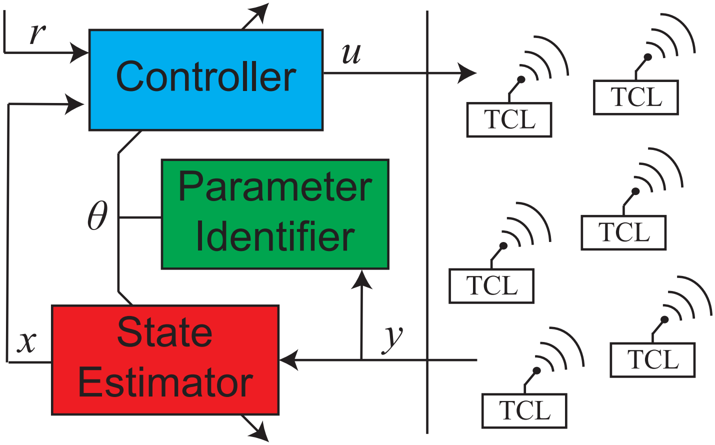
$$u(T_{\max},t) = q_1 v(T_{\max},t)$$
$$v(T_{\min},t) = q_2 u(T_{\min},t)$$

Original Idea: Malhame and Chong, Trans. on Automatic Control (1985)
Remark: Assumes homogeneous populations

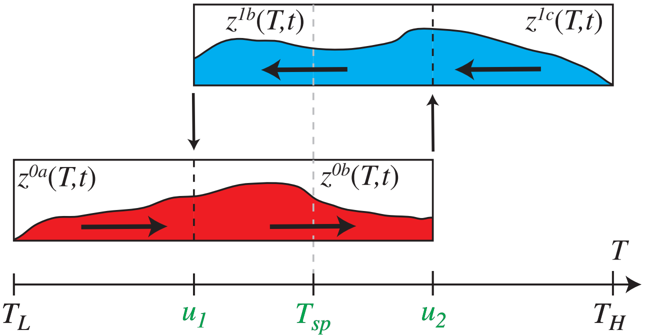
Model Comparison



Feedback Control System



Set-point / Deadband Control

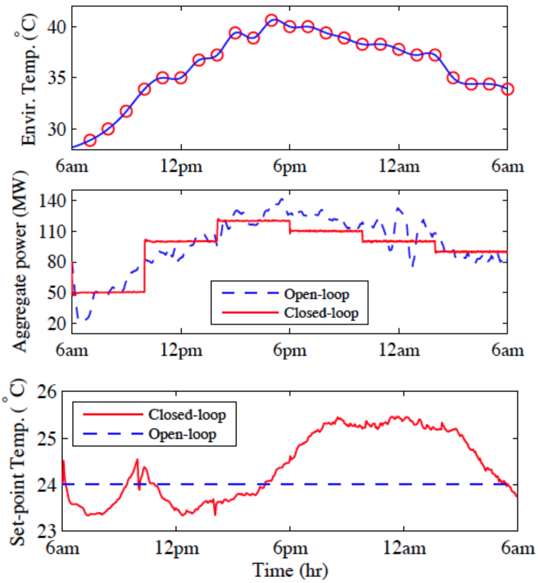


$$
\begin{aligned}
z_t^{1j}(T,t) &= \alpha\lambda(T) z_T^{1j}(T,t) + \alpha z^{1j}(T,t), \qquad j \in \{b,c\} \\
z_t^{0j}(T,t) &= -\alpha\mu(T) z_T^{0j}(T,t) + \alpha z^{0j}(T,t), \qquad j \in \{a,b\}
\end{aligned}
$$

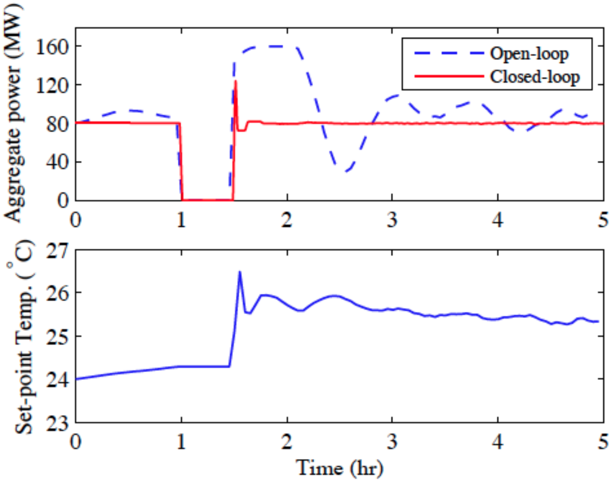
with boundary conditions

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

Aggregate Power Control



Aggregate Power Control



A Ghaffari, S. J. Moura, M. Krstic, "PDE-based Modeling, Control, and Stability Analysis of Heterogeneous Thermostatically Controlled Load Populations," *ASME Journal of Dynamic Systems, Measurement, and Control*, v 137, n 10, pp. 101009-101009-9.

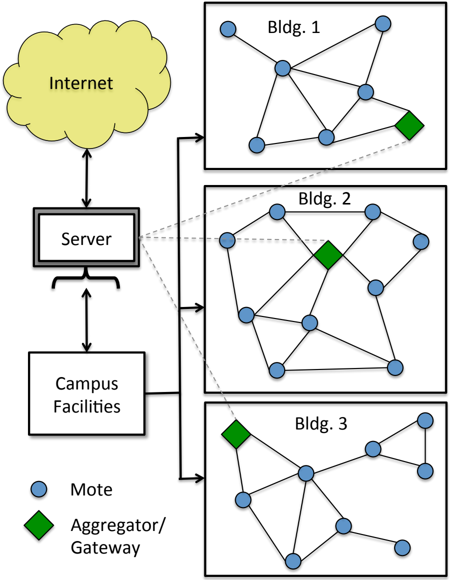

Pacific Ocean
Geisel Library
Jacobs Engineering Hall

UC San Diego Campus: A Living Laboratory

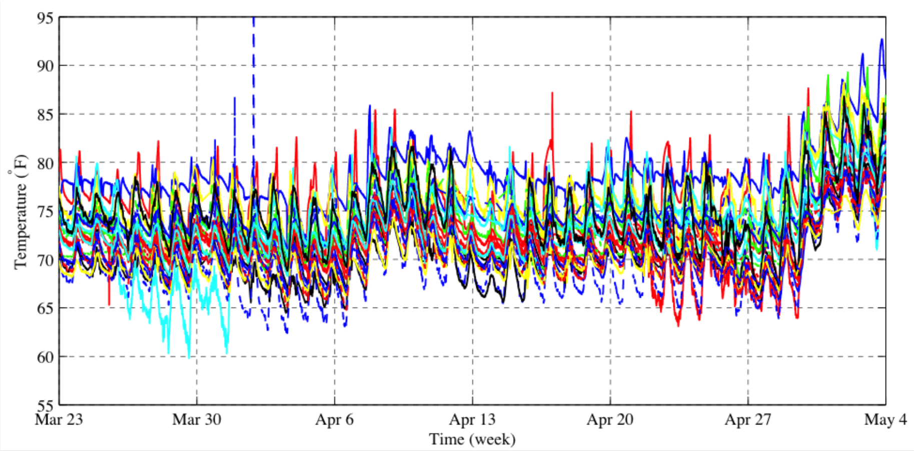
Goal: DR for Bldg Energy Mgmt

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

Sensor Nodes (Temp & Humidity)

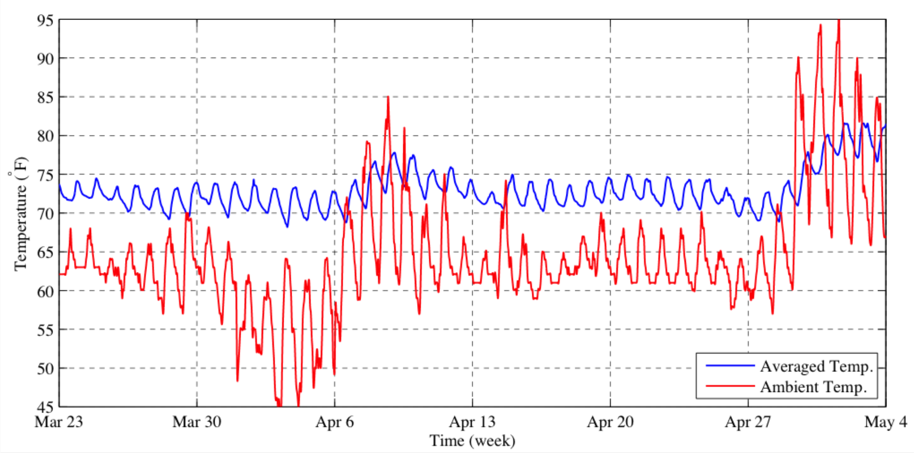


UCSD Office Temperature Data



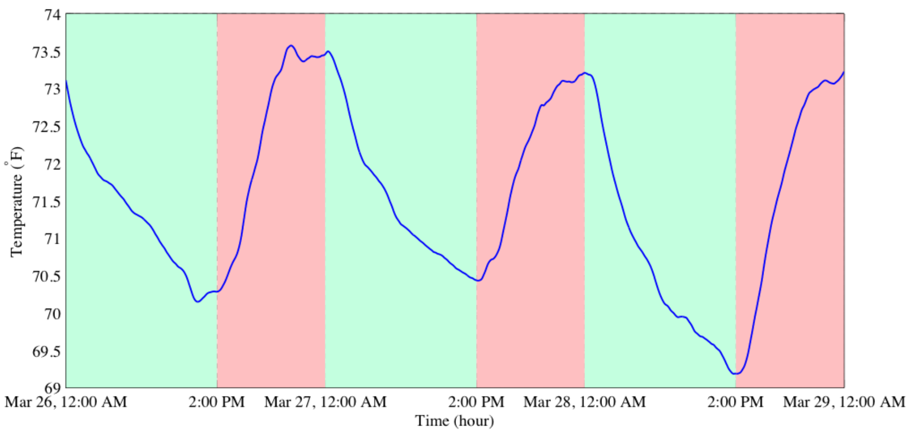
Temperature variation of monitored spaces over six week. The peak point of room temperature happens at midnight.

UCSD Office Temperature Data

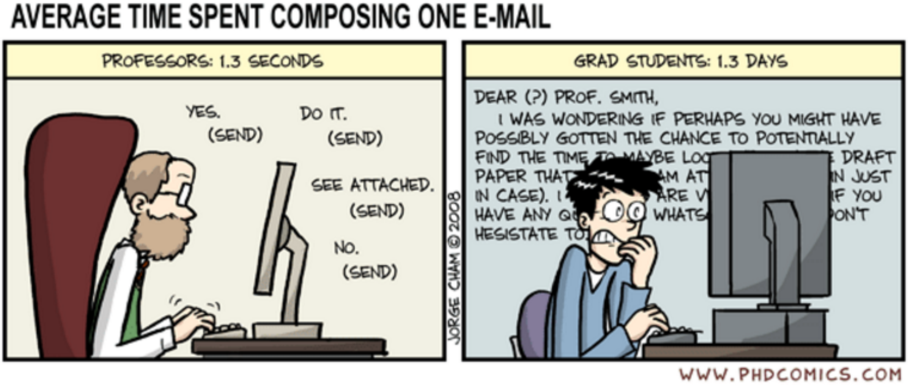


Temperature variation of monitored spaces over six week. The peak point of room temperature happens at midnight.

UCSD Office Temperature Data



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


AVERAGE TIME SPENT COMPOSING ONE E-MAIL
PROFESSORS: 1.3 SECONDS
YES.
(SEND)
DO IT.
(SEND)
SEE ATTACHED.
(SEND)
NO.
(SEND)
JORGE CHAM © 2008
GRAD STUDENTS: 1.3 DAYS
DEAR (?) PROF. SMITH,
I WAS WONDERING IF PERHAPS YOU MIGHT HAVE
POSSIBLY GOTTEN THE CHANCE TO POTENTIALLY
FIND THE TIME TO MAYBE LOO
DRAFT
PAPER THAT
AM AT
IN JUST
IN CASE). I
ARE V
IF YOU
HAVE ANY Q
WHATS
DON'T
HESITATE TO
WWW.PHDCOMICS.COM

The Demand-Side Management Problem

Needs: Integrate renewables AND enhance resilience/sustainability

Obstacle: Control populations of loads - stochastic, distributed, constrained

Definition (Flexible Loads):
Devices with controllable load profiles,
e.g. Electric vehicles, HVAC, electric water heaters, refrigerators

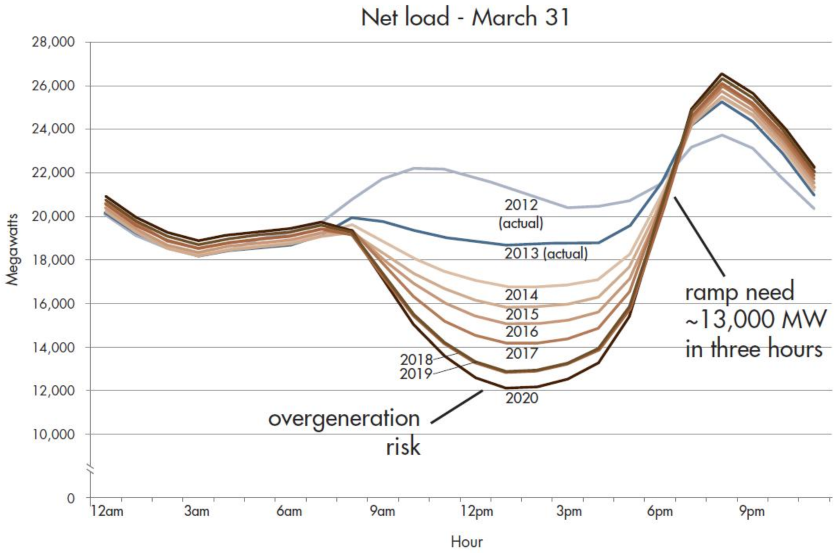
Some Interesting Facts

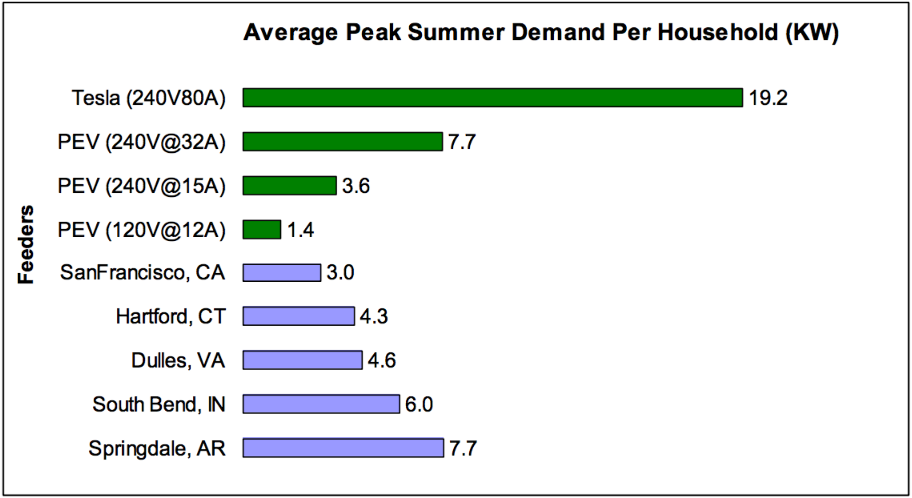
Plug-in Electric Vehicles (PEVs)	Potentially dispatchable loads “carbitrage” opportunity Firm variable renewables

The Punchline

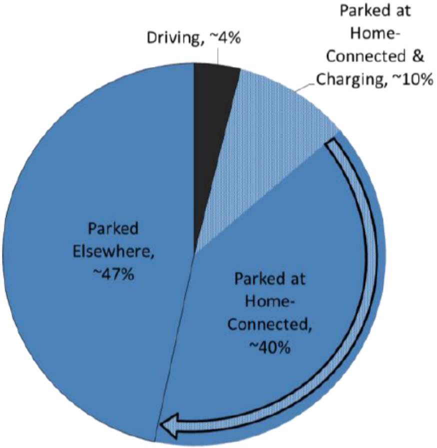
Exploit flexibility of PEV charging for power system reserves

The duck curve shows steep ramping needs and overgeneration risk




Average Peak Summer Demand Per Household (KW)
Feeders
Tesla (240V80A)
19.2
PEV (240V@32A)
7.7
PEV (240V@15A)
3.6
PEV (120V@12A)
1.4
SanFrancisco, CA
3.0
Hartford, CT
4.3
Dulles, VA
4.6
South Bend, IN
6.0
Springdale, AR
7.7

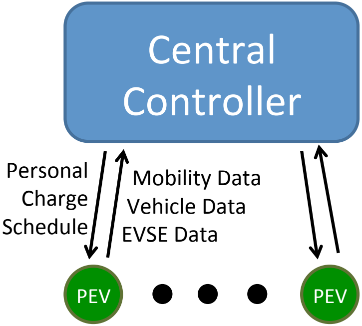
PEV Energy Storage: How much, when, and where?



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.

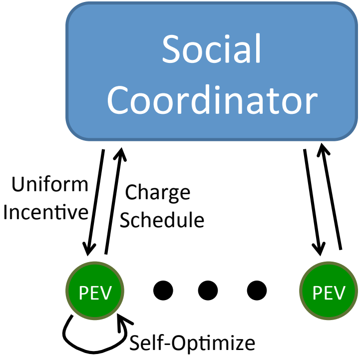
CENTRALIZED



+ Global optimality
+ Complete controllability

- Communication infrastructure
- Privacy concerns
- Scalability
- Modularity

DISTRIBUTED



+ Communication light
+ Privacy preserving
+ Modular
+ Scalable

- Lacks global optimality
- Analysis more difficult

Optimal PEV Aggregator Problem

$$
\begin{aligned}
\min_{u} \quad & \sum_{t=1}^{T} \left(D^t + \sum_{n=1}^{N} u_n^t \right)^2 \\
\text{s. to} \quad & (1 - R_n)^T u_n = 0, \qquad \forall n, \ \forall t \\
& \underline{P}_n^t \leq u_n^t \leq \overline{P}_n^t, \qquad \forall n, \ \forall t \\
& \text{[Battery Storage Dynamics]}
\end{aligned}
$$

A Quadratic Program (QP)

$T \times N$ optimization variables

$T \times N$ linear equality constraints

$4T \times N$ linear inequality constraints

Optimal PEV Aggregator Problem

$$
\begin{aligned}
\min_{u} \quad & \sum_{t=1}^{T} \left(D^t + \sum_{n=1}^{N} u_n^t \right)^2 \\
\text{s. to} \quad & (1 - R_n)^T u_n = 0, \qquad \forall n,\ \forall t \\
& \underline{P}_n^t \leq u_n^t \leq \overline{P}_n^t, \qquad \forall n,\ \forall t \\
& \text{[Battery Storage Dynamics]}
\end{aligned}
$$

A Quadratic Program (QP)	100K EVs*, 24 hrs
$T \times N$ optimization variables	2.4M
$T \times N$ linear equality constraints	2.4M
$4T \times N$ linear inequality constraints	9.6M

*cumulative PEVs sold in CA by mid-2014

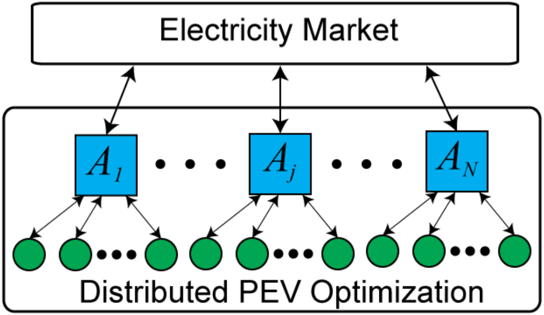
Optimal PEV Aggregator Problem

$$\begin{aligned} \min_{u} \quad & \sum_{t=1}^{T} \left(D^t + \sum_{n=1}^{N} u_n^t \right)^2 \\ \text{s. to} \quad & (1 - R_n)^T u_n = 0, \qquad \forall n,\ \forall t \\ & \underline{P}_n^t \leq u_n^t \leq \overline{P}_n^t, \qquad \forall n,\ \forall t \\ & \text{[Battery Storage Dynamics]} \end{aligned}$$

A Quadratic Program (QP)	1.5M EVs*, 24 hrs
$T \times N$ optimization variables	32M
$T \times N$ linear equality constraints	32M
$4T \times N$ linear inequality constraints	144M

*Gov. Brown 2025 ZEV Goal

Distributed Optimization via Dual Splitting



$$\max_{\mu} \frac{-\|\mu\|^2}{4} + \mu^T D \quad + \quad \sum_{n}^{N} \min_{u_n} \mu^T u_n + \sigma \|u_n\|^2$$

$$\text{s. to} \quad L_n \leq B u_n \leq M_n$$

$$A_n u_n = 0$$

μ is time-varying price incentive uniformly provided to each PEV owner.

Distributed Optimization via Dual Splitting

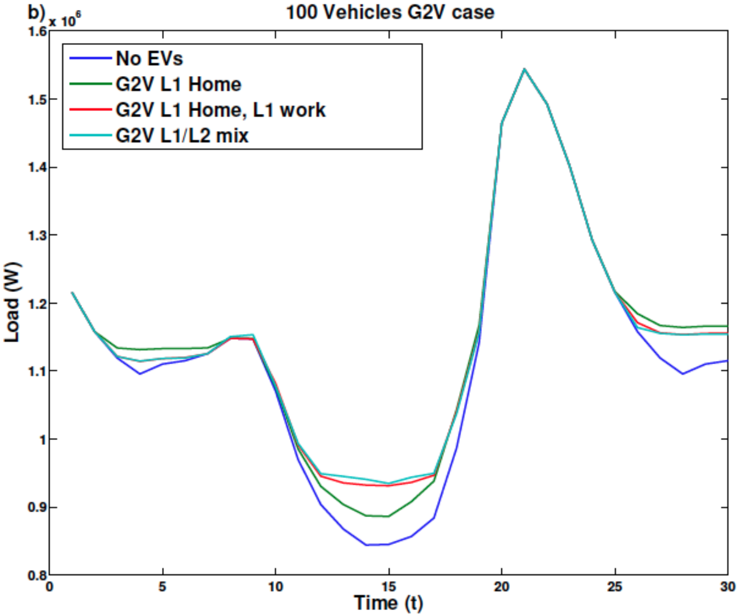
$$\max_{\mu} \frac{-\|\mu\|^2}{4} + \mu^T D \quad + \quad \sum_{n}^{N} \min_{u_n} \mu^T u_n + \sigma \|u_n\|^2$$

$$\text{s. to} \quad L_n \leq B u_n \leq M_n$$

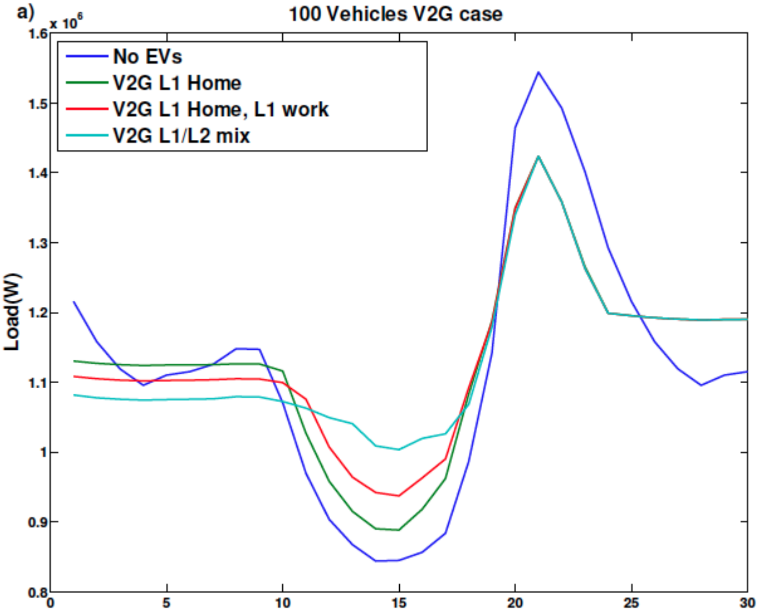
$$A_n u_n = 0$$

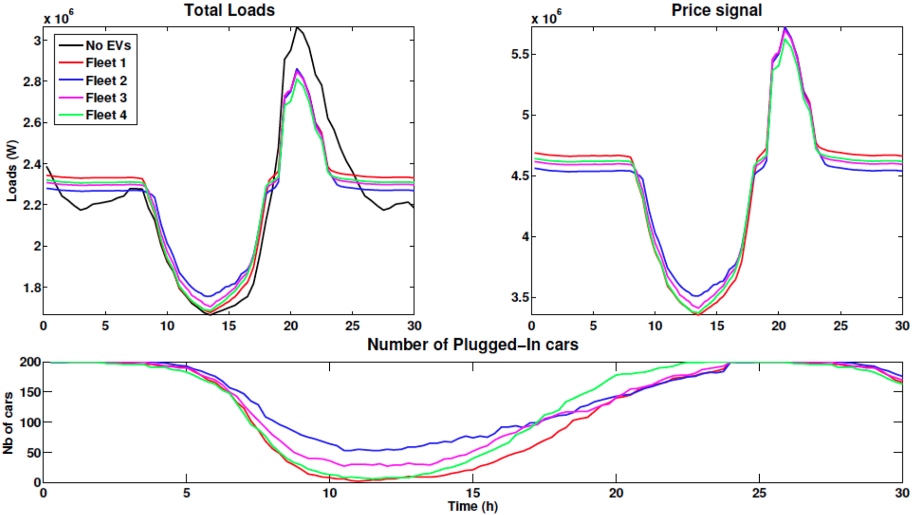
μ is time-varying price incentive uniformly provided to each PEV owner.

Outer (Aggregator) QP	**Inner (PEV) QP (N in parallel)**
T optimization variables	T optimization variables
0 linear equality constraints	T linear equality constraints
0 linear inequality constraints	$4T$ linear inequality constraints



b)
100 Vehicles G2V case
x 10^6
No EVs
G2V L1 Home
G2V L1 Home, L1 work
G2V L1/L2 mix
Load (W)
Time (t)
0.8
0.9
1
1.1
1.2
1.3
1.4
1.5
1.6
0
5
10
15
20
25
30


a)
100 Vehicles V2G case
x 10^6
No EVs
V2G L1 Home
V2G L1 Home, L1 work
V2G L1/L2 mix
Load(W)
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0
5
10
15
20
25
30



C. Le Floch, F. Belletti, S. Saxena, A. Bayen, S. J. Moura, "Distributed Optimal Charging of Electric Vehicles for Demand Response and Load Shaping," *54th IEEE Conference on Decision and Control*, Osaka, Japan, 2015.

Reading Materials

- S. J. Moura, J. Bendsten, V. Ruiz, "Parameter Identification of Aggregated Thermostatically Controlled Loads for Smart Grids using PDE Techniques," *International Journal of Control*, v 87, n 7, pp. 1373-1386, May 2014.
- A Ghaffari, S. J. Moura, M. Krstic, "PDE-based Modeling, Control, and Stability Analysis of Heterogeneous Thermostatically Controlled Load Populations," *ASME Journal of Dynamic Systems, Measurement, and Control*, v 137, n 10, pp. 101009-101009-9.
- S. J. Moura, V. Ruiz, J. Bendsten, "Modeling Heterogeneous Populations of Thermostatically Controlled Loads using Diffusion-Advection PDEs," *ASME Dynamic Systems and Control Conference*, Stanford, CA, 2013.
- S. J. Moura, J. Bendsten, V. Ruiz, "Observer Design for Boundary Coupled PDEs: Application to Thermostatically Controlled Loads in Smart Grids." *52nd IEEE Conference on Decision and Control*, Florence, Italy, 2013. (Invited Paper)
- C. Le Floch, F. Belletti, S. Saxena, A. Bayen, S. J. Moura, "Distributed Optimal Charging of Electric Vehicles for Demand Response and Load Shaping," *54th IEEE Conference on Decision and Control*, Osaka, Japan, 2015.
- C. Le Floch, F. Di Meglio, S. J. Moura, "Optimal Charging of Vehicle-to-Grid Fleets via PDE Aggregation Techniques," *2015 American Control Conference*, Chicago, IL, 2015.

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ZERO MOTORCYCLES
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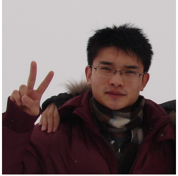
SolarCity
stem
SAMSUNG
BOSCH
chargepoint
Ford
BERKELEY LAB
Lawrence Berkeley National Laboratory
State of California Energy Commission
BMW
Mercedes-Benz
Statoil
MITSUBISHI ELECTRIC RESEARCH LABORATORIES
RECARGO
Renewable Energies • Electric Car • Grid Optimization

Our Team at UC Berkeley

Dr. Satadru Dey

Hector Perez

Caroline Le Floch



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eCAL
energy, controls, & applications lab

APPENDIX SLIDES