Recent Advances in Controls Research for Smart Energy Systems

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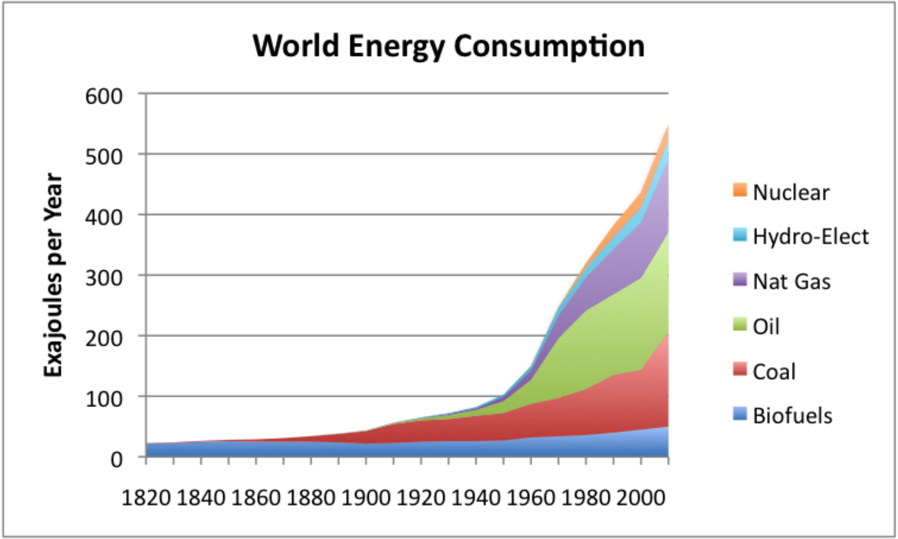
Cymer Center for Control Systems and Dynamics
UC San Diego

January 10, 2013



Vaclav Smil Estimates from Energy Transitions

A New Energy Infrastructure

2013 CA Efficient Building Standards:

- PV-ready rooftops
- Adaptive lighting and HVAC, demand response-ready

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White House Energy Initiatives:

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- SunShot, EV Everywhere

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Regulatory Targets:

- CA: 33% renewables by 2020 (14.5% in 2011)
- US: 20% wind penetration by 2030 (3% in 2011)
- Denmark: 50% wind penetration by 2025

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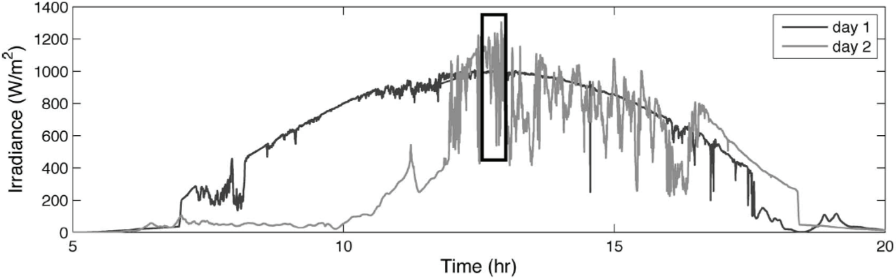
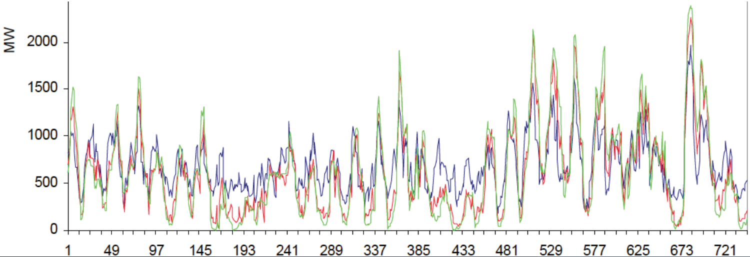
How will we meet these aggressive targets?

Renewables are Variable

Solar Data: Brunton, Rowley, Kulkarni, Clarkson, IEEE TIE, 2010



Wind Data: NYSERDA Wind Forecasts, Aug 2001



Integrating Renewables

Grid requires 4 GW of additional ancillary services to maintain stability
Traditional A/S provided by thermal generation, i.e. fossil fuels

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TCLs comprise 50% of electricity consumption in the US

Source: Energy Information Administration, “Residential energy consumption survey,” US DOE, Tech. Rep., 2001.

“Only 11% of thermostats are programmed.” - EPA via Matt Rogers

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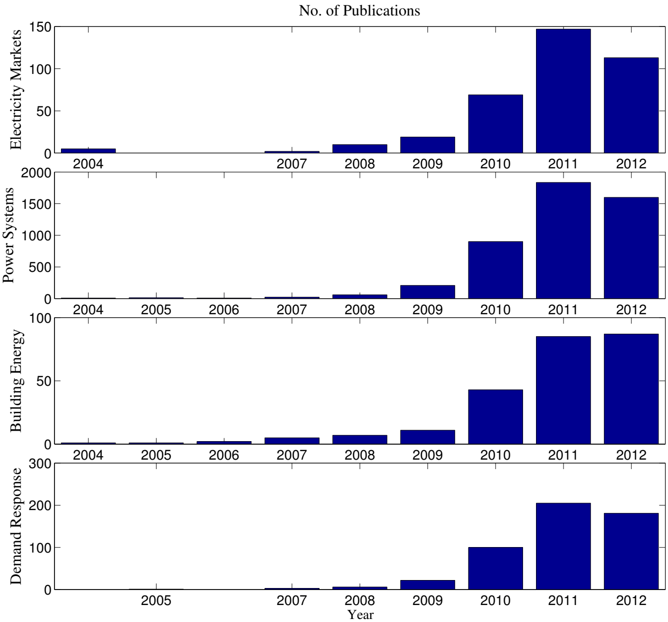
Four Dimensions of Smart Grids			
Electricity Markets	Power Systems	Building Energy	Demand Response

Hot Research Topics in “Smart Grids”



Some Top Researchers in our Community

incomplete...

Electricity Markets	Annaswamy [MIT], Bitar [Cornell], Dahleh [MIT], Meyn [Florida], Poolla [UC Berkeley]
Power Systems	Bullo [UCSB], Chakrabortty [NCSU], Dominguez-Garcia [Illinois], Hiskens [Michigan], Low [Caltech]
Building Energy Systems	Alleyne [Illinois], Borrelli [UC Berkeley], Hencey [Cornell], Mezic [UCSB], Morari [ETH Zurich]
Demand Response	Auslander [UC Berkeley], Callaway [UC Berkeley], Fathy [Penn State], Ilić [CMU], Zhang [Ohio State]

Demand Response via Thermostatically Controlled Loads

Punch Line

Flexible loads can absorb variability in renewable generation

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Flexible loads

- TCLs, e.g. HVAC, water heaters
- Dispatchable loads, e.g. EVs, appliances

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Value to stakeholders

Player	Value
Flexible Loads	discounted electricity price
Utilities	better forecasting
Aggregator	minimize operating costs
Renewable Generators	firming variable power
System Operator	displacing reserve capacity

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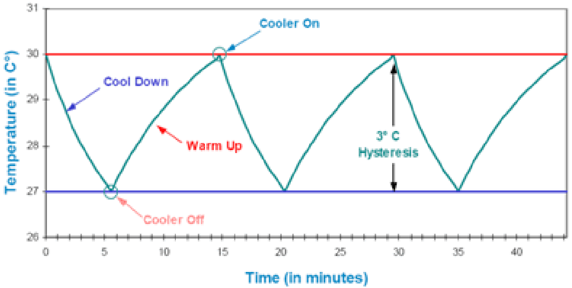
Problem Statement

How to exploit load flexibility to track renewable generation?

Modeling TCLs



$$\dot{T}_i(t) = \frac{1}{R_i C_i}\left[T_\infty - T_i(t) - s_i(t) R_i P_i\right], \quad i = 1, 2, \ldots, N$$

$$s_i(t) = \begin{cases} 0 & \text{if } s_i(t^-) = 1 \wedge T_i(t) \leq T_{\min,i} \\ 1 & \text{if } s_i(t^-) = 0 \wedge T_i(t) \geq T_{\max,i} \\ s_i(t^-) & \text{otherwise} \end{cases}$$

$$P(t) = \sum_i^N \frac{1}{\eta_i} P_i s_i(t)$$

Modeling Aggregated TCLs

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

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

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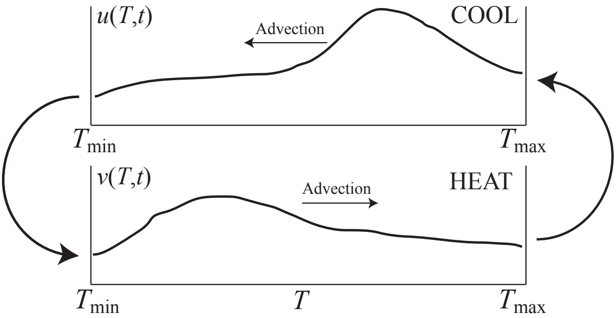
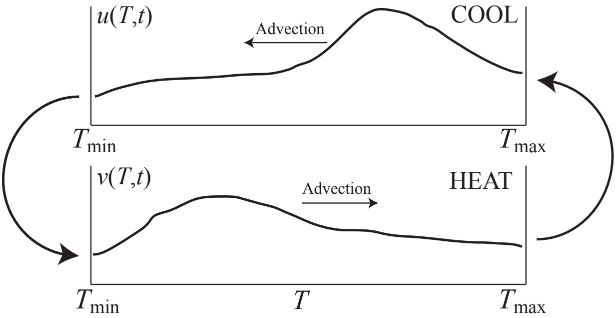


Modeling Aggregated TCLs



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

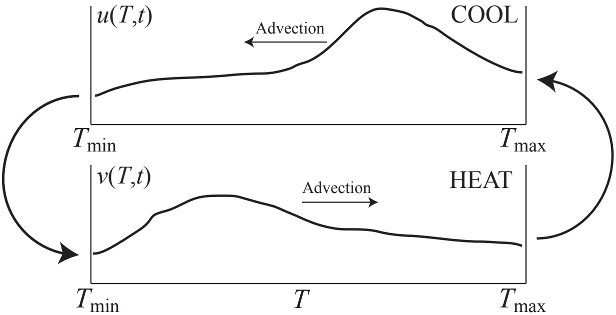
$$v_t(T,t) = -\alpha\mu(T) v_T(T,t) + \alpha v(T,t)$$

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

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

$$P(t) = \frac{1}{\eta}\int_{T_{\min}}^{T_{\max}} u(T,t)\,dT$$

Modeling Aggregated TCLs



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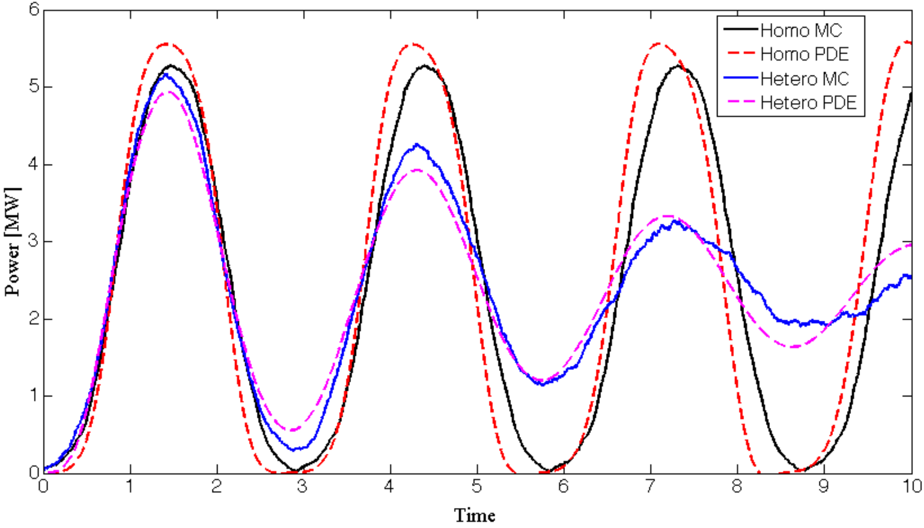
Remark: Assumes homogeneous populations

Modeling Heterogeneous Aggregated TCLs

Reality: TCL populations are heterogeneous
e.g. variable heat capacity, power, deadband sizes

$$
\begin{aligned}
u_t(T,t) &= \alpha\lambda(T)u_T(T,t) + \alpha u(T,t) + \beta u_{TT}(T,t) \\
v_t(T,t) &= -\alpha\mu(T)v_T(T,t) + \alpha v(T,t) + \beta v_{TT}(T,t) \\
u(T_{\max},t) &= q_1 v(T_{\max},t), \qquad u_T(T_{\max},t) = -v_T(T_{\max},t) \\
v(T_{\min},t) &= q_2 u(T_{\min},t), \qquad v_T(T_{\min},t) = -u_T(T_{\min},t)
\end{aligned}
$$

Model Comparison



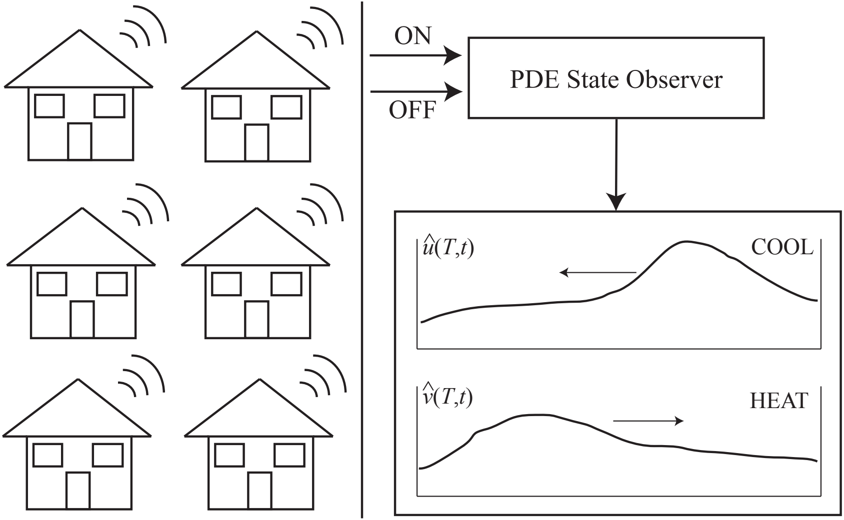
Monitoring w/ Minimal Communication

Leveraging Physics and Estimation Theory

Reconstruct $u(T,t), v(T,t)$	Monitor aggregate temperature dynamics
Measure $u(T_{\max},t), v(T_{\min},t)$ only	Receive ON/OFF signal only

Monitoring w/ Minimal Communication

Leveraging Physics and Estimation Theory



Control Options

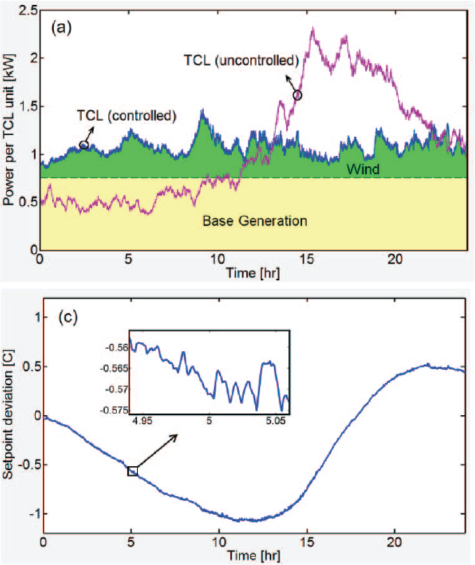
Price Signals

Direct Load Control

- Temperature setpoint
- Temperature deadband
- Direct switching

Wind Power Tracking

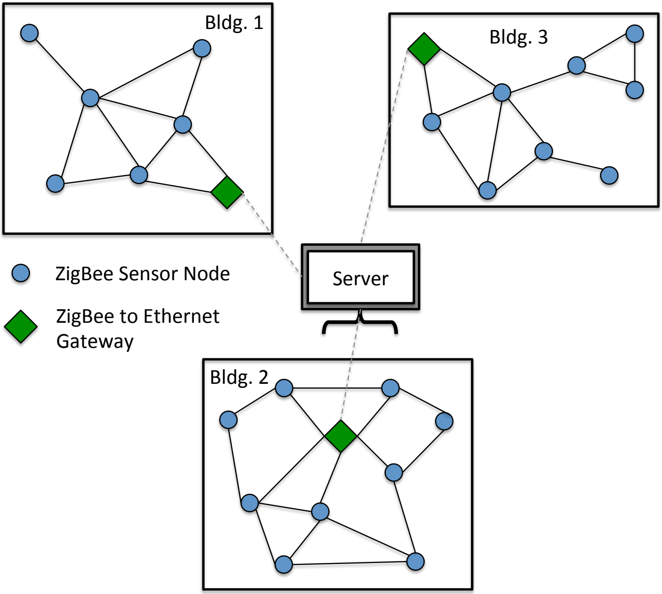
Bashash & Fathy, IEEE TCST, 2011



- 1000 TCLs, 10.5 MW wind
- Tracking Error $< 1\%$
- Setpoint changes $\approx \pm 1^\circ C$

UCSD Campus - A Demand Response Laboratory

Future: TCL Wireless Sensor Network



Project Summary

Year 1: Estimation

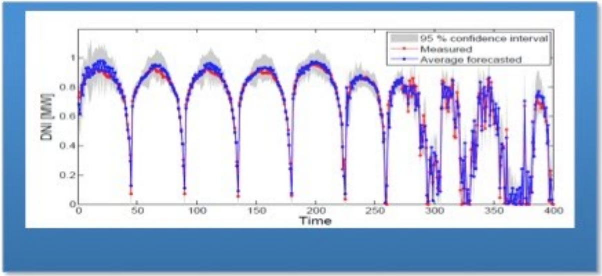
- Finalize wireless sensor node design
- Test 5-node micro-network
- Deploy 100-node network
- Verify estimation algorithms

Year 2: Control

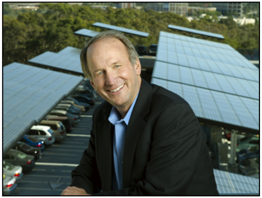
- Design control theory
- Finalize actuation architecture
- Verify control algorithms

Solar Forecasting

Carlos Coimbra
Associate Professor
Solar Forecast Engine Lab



Leadership @ UCSD



Byron Washom
Director of Strategic Energy Initiatives
@UCSDEnergy

Miroslav Krstic
Associate Vice Chancellor for Research
Director of Cymer Center
for Control Systems and Dynamics

John Dilliott
Campus Energy and Utilities Director

Discussion

- Value of research for Nest Labs
- Consultation on “sanitized” technical issues
- Bilateral transfer of knowledge

Acknowledgements:
Prof. Jan Bendsten, Aalborg University, Denmark
Victor Ruiz, UCSD

Thanks for your attention!
Questions?

Publications available at
http://flyingv.ucsd.edu/smoura/

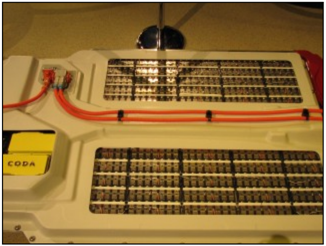
Collaboration with Nest Labs

- Letter of Support for Energy Innovations Small Grant Program (Due Feb 5)
- Bilateral knowledge transfer
- Support as opportunities emerge

Open Problems in Energy Storage and Control

Battery Management Systems

- Modeling & Identification
- SOC/SOH Estimation
- Constrained Control
- ...



Open Problems in Energy Storage and Control

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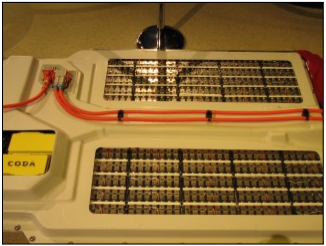
Energy Storage in Smart Grid

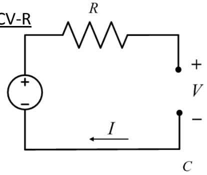
- Modeling & Design
- Hierarchical Control Framework
- Renewables
- ...



Battery Models

Equivalent Circuit Model

(a) OCV-R



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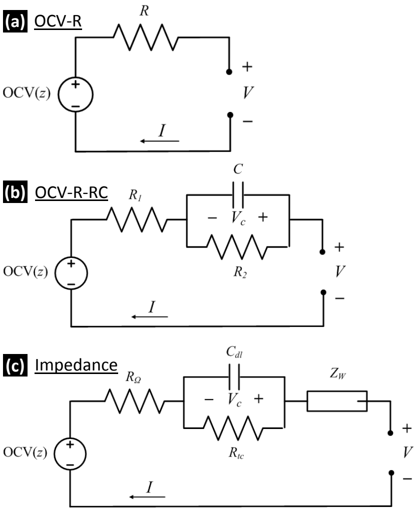

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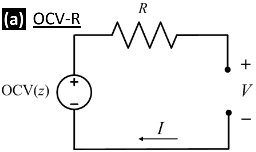
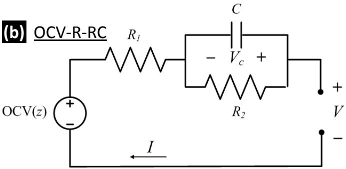
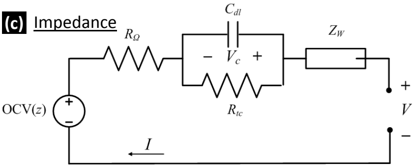


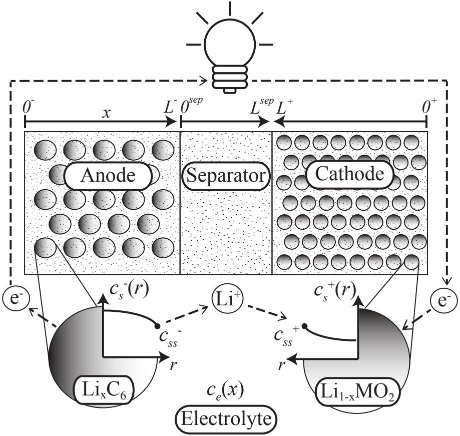
(b) OCV-R-RC



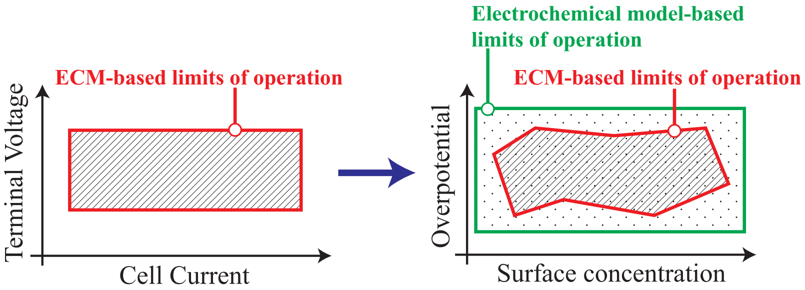
(c) Impedance



Electrochemical Model



Operate Batteries at their Physical Limits



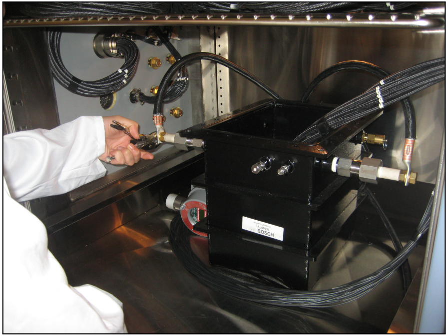
Electrochemical Model Equations

well, some of them

Description	Equation
Solid phase Li concentration	$\frac{\partial c_s^\pm}{\partial t}(x,r,t) = \frac{1}{r^2}\frac{\partial}{\partial r}\left[D_s^\pm r^2 \frac{\partial c_s^\pm}{\partial r}(x,r,t)\right]$
Electrolyte Li concentration	$\varepsilon_e \frac{\partial c_e}{\partial t}(x,t) = \frac{\partial}{\partial x}\left[\varepsilon_e D_e \frac{\partial c_e}{\partial x}(x,t) + \frac{1-t_c^0}{F} i_e^\pm(x,t)\right]$
Solid potential	$\frac{\partial \phi_s^\pm}{\partial x}(x,t) = \frac{i_e^\pm(x,t) - I(t)}{\sigma^\pm}$
Electrolyte potential	$\frac{\partial \phi_e}{\partial x}(x,t) = -\frac{i_e^\pm(x,t)}{\kappa} + \frac{2RT}{F}(1-t_c^0)\left(1 + \frac{d\ln f_{c/a}}{d\ln c_e}(x,t)\right)\frac{\partial \ln c_e}{\partial x}(x,t)$
Electrolyte ionic current	$\frac{\partial i_e^\pm}{\partial x}(x,t) = a_s F j_n^\pm(x,t)$
Molar flux btw phases	$j_n^\pm(x,t) = \frac{1}{F} i_0^\pm(x,t)\left[e^{\frac{\alpha_a F}{RT}\eta^\pm(x,t)} - e^{-\frac{\alpha_c F}{RT}\eta^\pm(x,t)}\right]$
Temperature	$\rho c_P \frac{dT}{dt}(t) = h\left[T^0(t) - T(t)\right] + I(t)V(t) - \int_{0^-}^{0^+} a_s F j_n(x,t)\Delta T(x,t)dx$

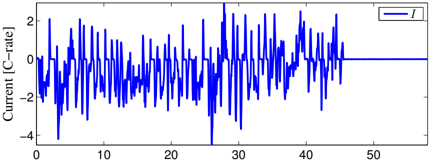
Animation of Li Ion Evolution

Experimental Testing at Bosch RTC



Results

UDDS Drive Cycle Input



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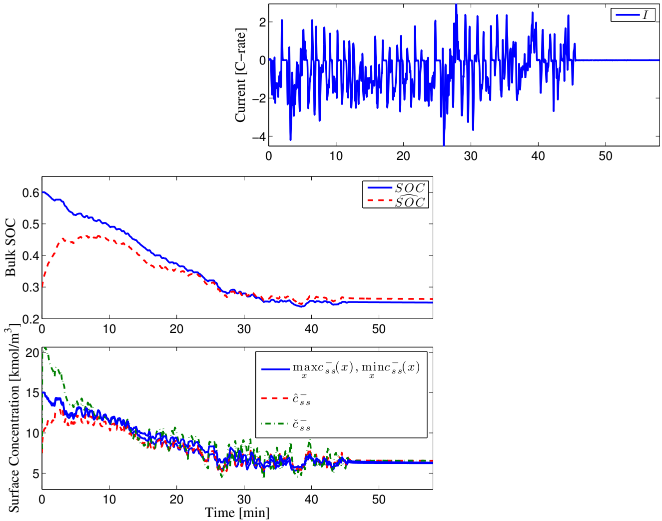

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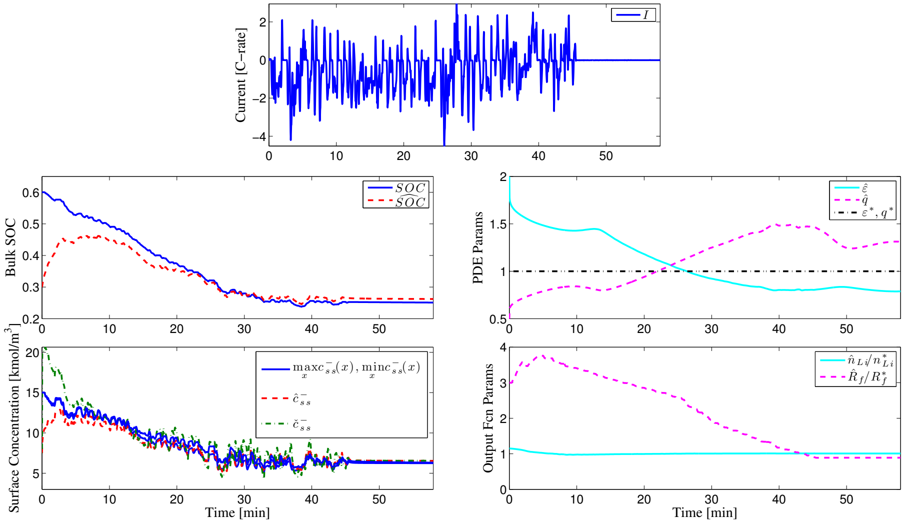
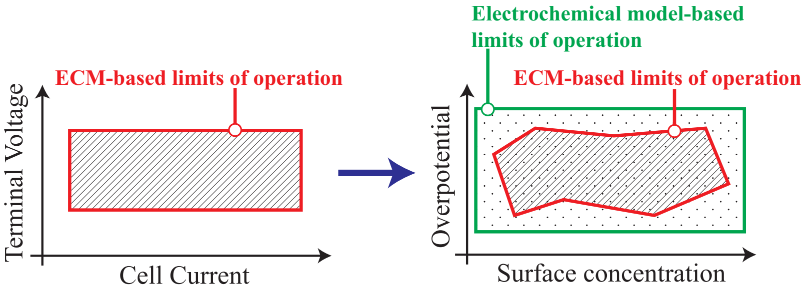


Operate Batteries at their Physical Limits

Problem Statement

Given accurate state estimates, govern the electric current such that safe operating constraints are satisfied.

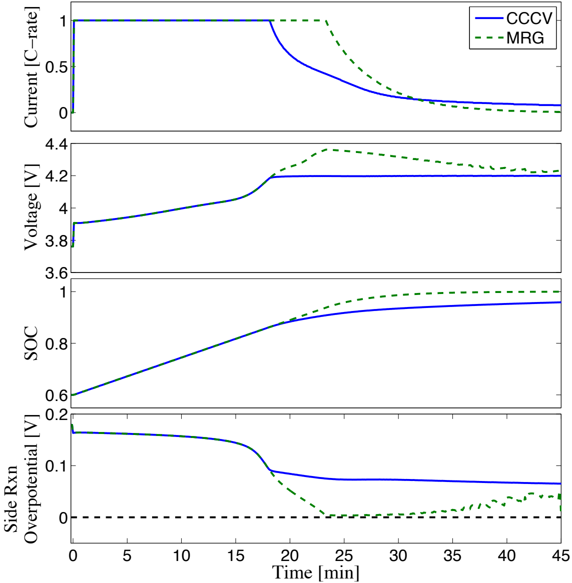


Constraints

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 $y_{\min} \leq y \leq y_{\max}$.

Application to Charging



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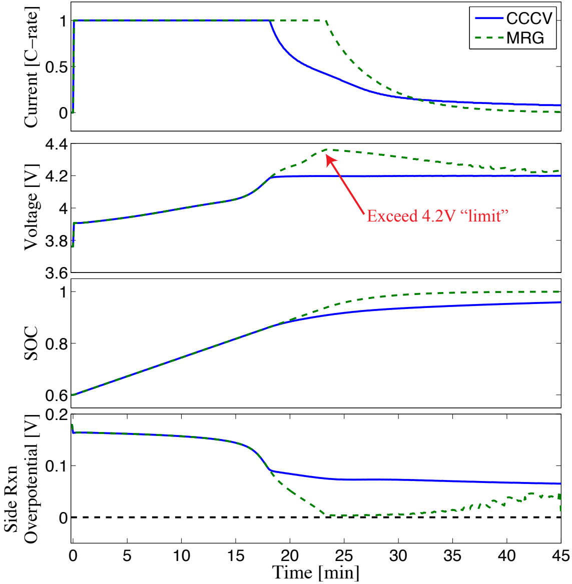

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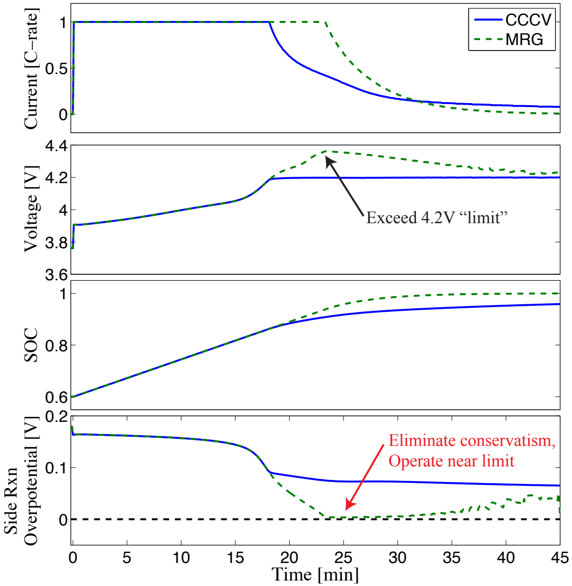

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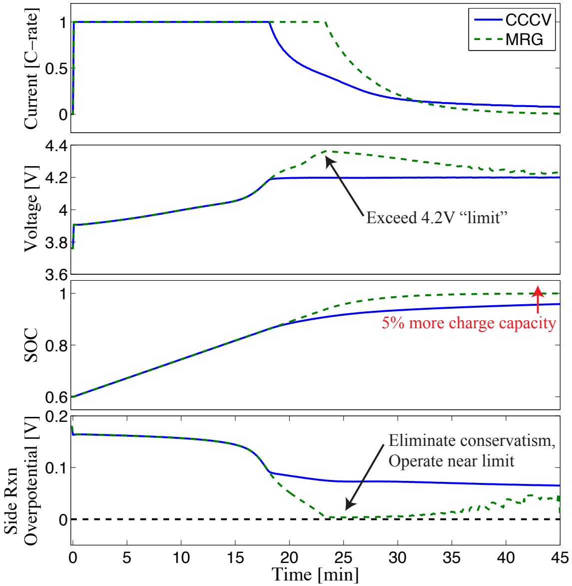

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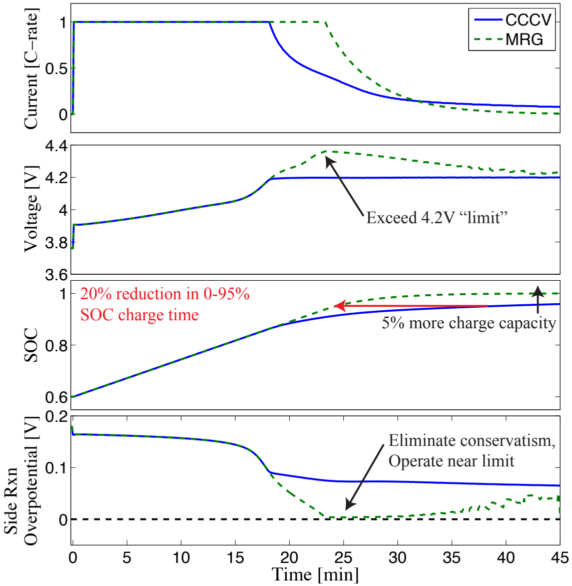

Demand Response of Aggregated Storage

Joint Work with Jan Bendsten, Aalborg University, Denmark