Aggregated Electricity Load Modeling & Control for Regulation and Load Following Ancillary Services

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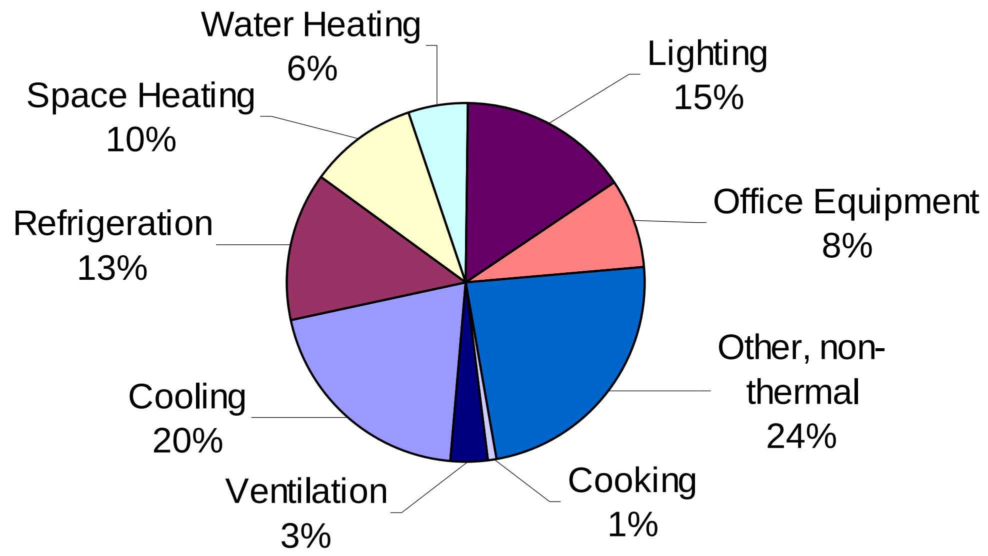
Thermostatically Controlled Loads (TCLs)

- 50% of commercial and residential electricity is consumed by thermal loads in the United States.

- Hysteresis control typical (on / off)



- Exact time of operation doesn't matter to user

- Aggregated demand =

  $\sum(\text{duty cycle})\times(\text{peak demand})$

  …due to system diversity

- "Latent" source of energy storage, with efficiency near 100%

PCTs and AMI

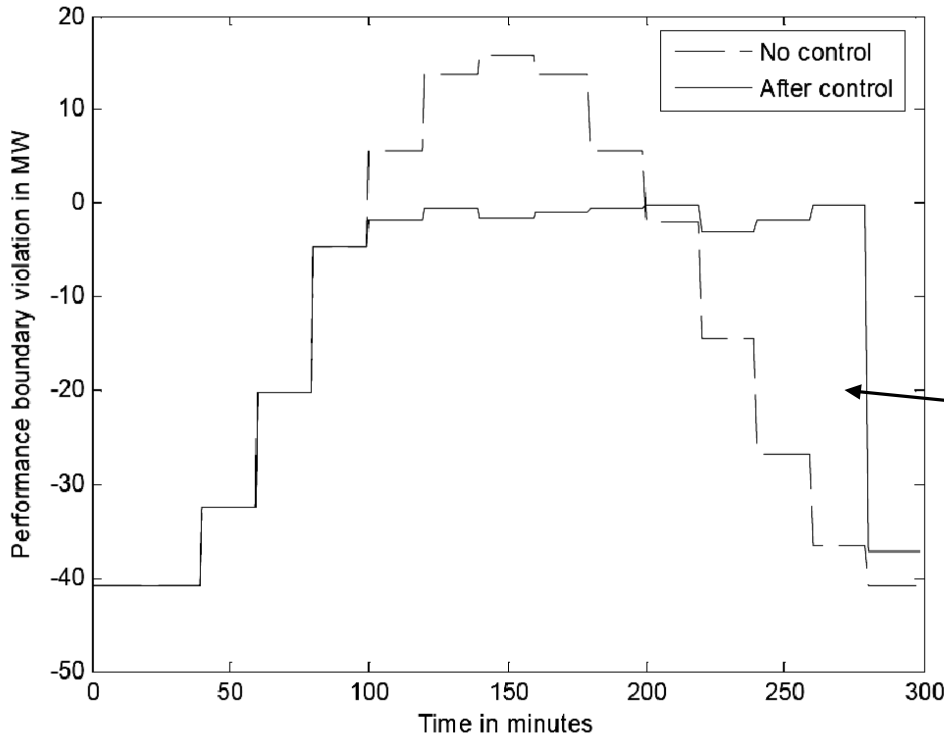
- PCT = Programmable Communicating Thermostat
  - Remote manipulation of temperature set point
  - Potential for high resolution response for utility
  - May appeal to mass market for convenience

- AMI = Advanced Metering Infrastructure
  - Can communicate with all loads
  - But also requires hardware on load

Conventional Load Control

- Interrupt power to loads with relays

Source: Vittal and Ramanathan, "Security Enhancement through Direct Non-Disruptive Load Control" Final Project Report Part II. PSERC Publication 06-02



"Energy payback"

- Previous research focuses on:
  - Optimal control (e.g. Bhattacharyya & Crow 1996)
  - MPC approaches (e.g. Molina *et al* 2000)
- But there are challenges: system identification is one…

Challenges with Load Control

The California Energy Commission proposed in January 2008 to require PCTs on all new construction. The response:

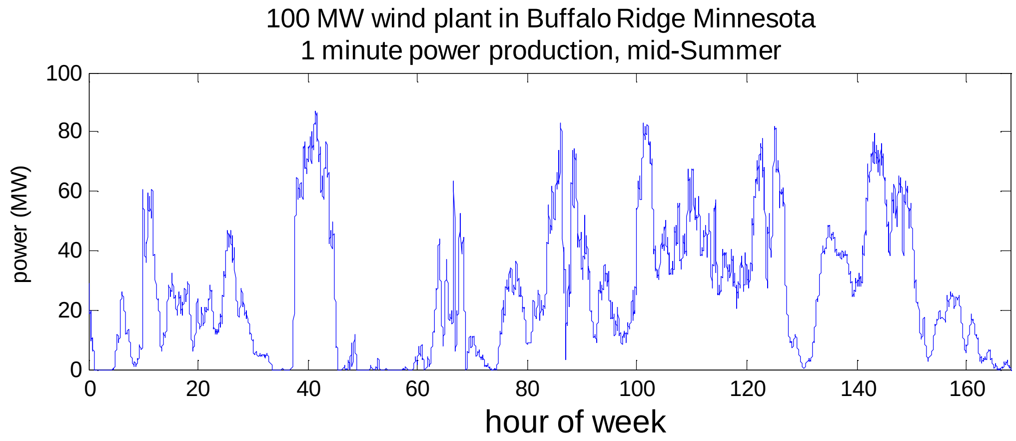
"There will be governors or limits on your thermostat from the utility company, and it will be whatever the state mandates…If we're not careful, this is the kind of stuff we're going to elect people to start implementing all over the country."

- Rush Limbaugh, January 9, 2008

Are there alternative applications?

- Can we get value without compromising end-use function?
- Possible answer: balance shorter time scale fluctuations via partial synchronization

> *"Energy storage is key to expanding the use of renewable energy…. The technology we're testing has the potential to reduce the impact caused by the variability and limited predictability of wind and solar generation."* - Xcel Energy brochure



The feasibility of coupling sodium sulfur batteries with wind farms is being studied in Minnesota (Xcel Energy)

Load Modeling and Control:

This work will focus on:

- Thermostat control (not relays)
  - controlling end-use function, not the desired power consumption level
- Small perturbations in operating state → low impact on end-user
- Developing methods amenable to (or not requiring) system ID and feedback control
- Managing variable output from renewables
- Identifying design parameters for load control program

Modeling individual TCLs

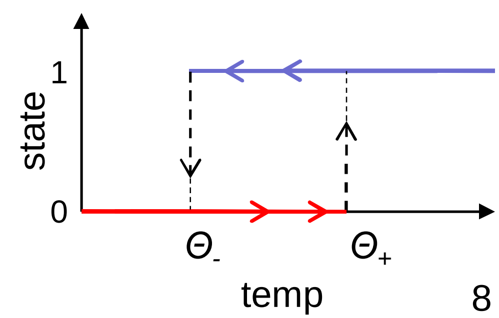
$$\theta_i = \text{temperature of } i^{\text{th}} \text{ load}$$

$$m_i \in \{0,1\} = \text{ state of load}$$

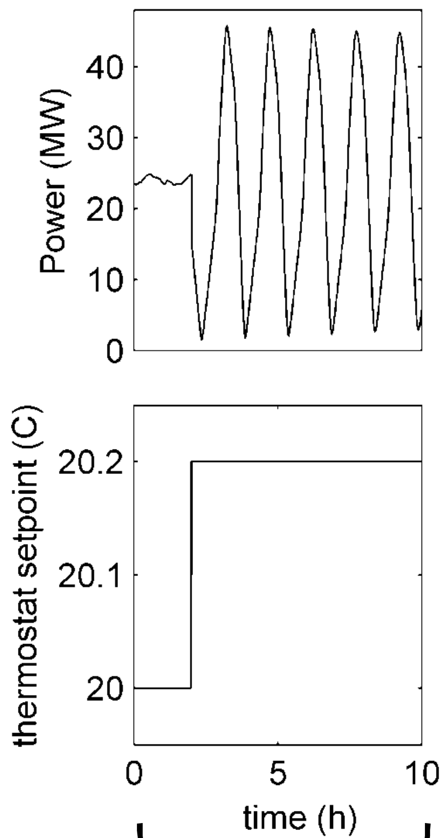
cooling model

$$C_i \frac{d\theta_i(t)}{dt} = -\frac{1}{R_i}\left(\theta_i(t) - \theta_a\right) - m_i(t) P_i + w_i(t)$$

Thermal capacitance, resistance and heat gain are heterogeneous



Aggregated response to setpoint change

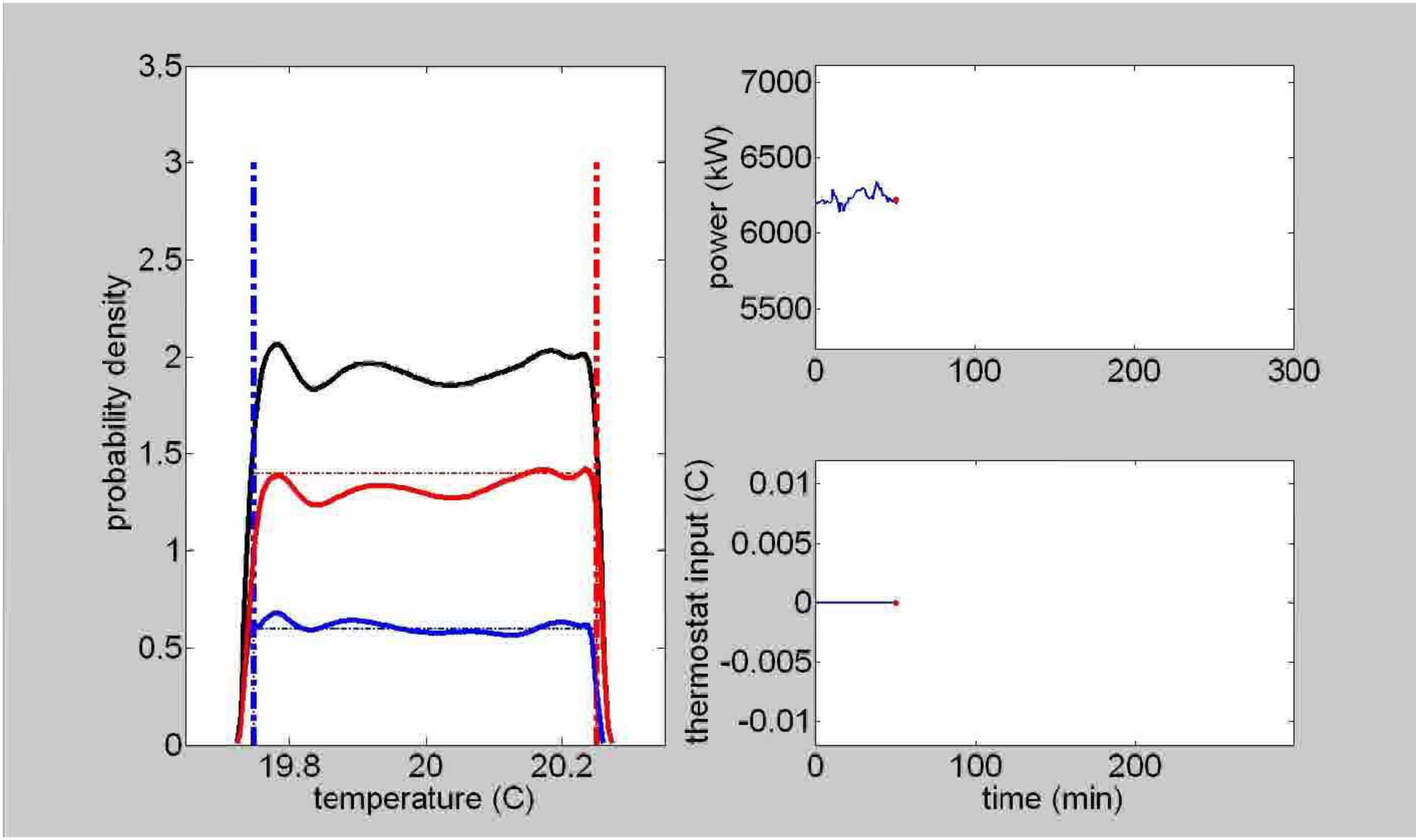


No parameter heterogeneity; limited damping from noise term

Discretized individual model, 10,000 simulated simultaneously, coupled by setpoint change

Load Modeling and Control:

Evolution of the PDF



Load Modeling and Control:

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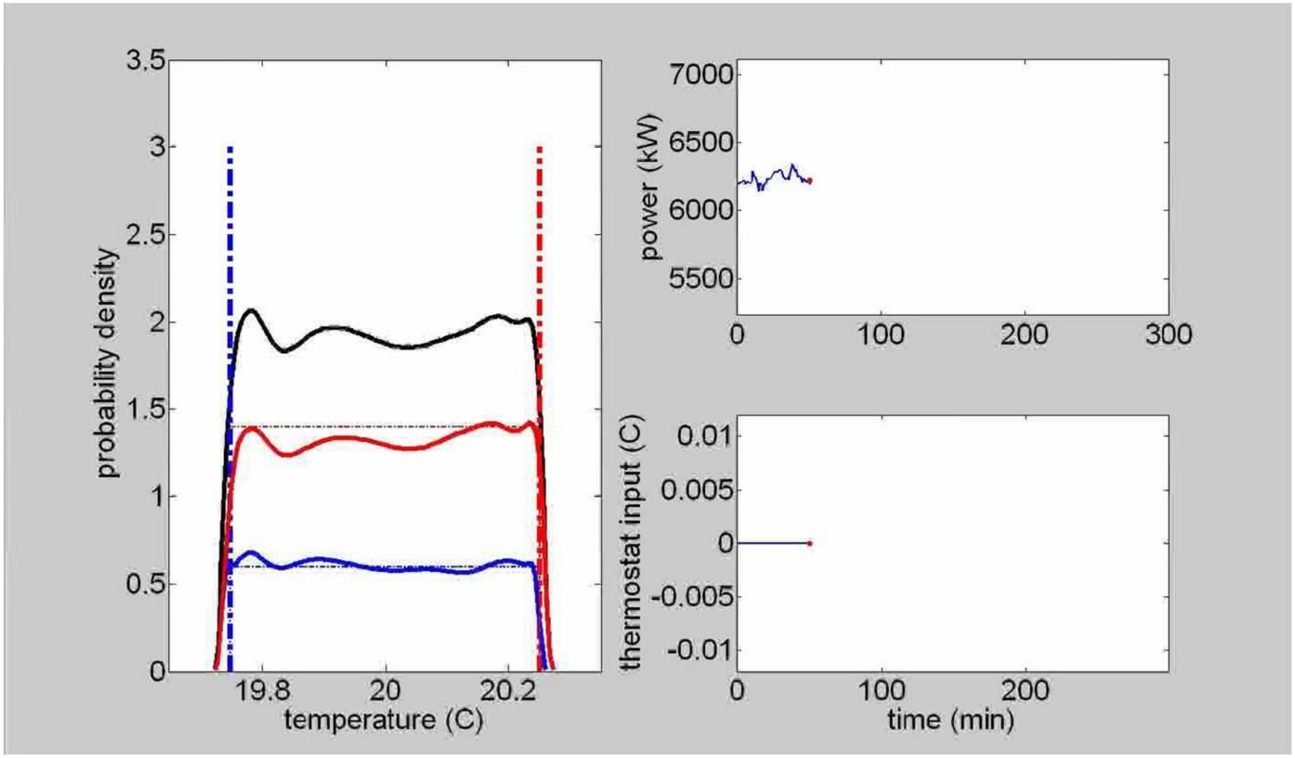


- Observation: distributions are near steady state at the deadband limits
- Changes in power demand are due to partial load sync.
- Prediction: characteristics that dissipate disturbances will improve performance

Linear Approximation

- Assume *uniform* steady state probability distribution
- Assume small process noise term, w_i
- Model response to change in setpoint, Δu_t
- Then it is straightforward to show that the change in power demand is:

$$\Delta y^{ss}_{t_{n+1}} = -\frac{\Delta u_{t_n}}{\delta} \sum_i \frac{1}{\eta} P_i$$

- If disturbances from steady state are stochastic

$$\Delta y_{t_{n+1}} = -\frac{\Delta u_{t_n}}{\delta} \sum_i \frac{1}{\eta_i} P_i + e_{t_n}$$

- The linear model is a submodel of the ARMAX time series model:

$$A(q)\, y_{t_n} = B(q)\, u_{t_n} + C(q)\, e_{t_n}$$

Time series model performance

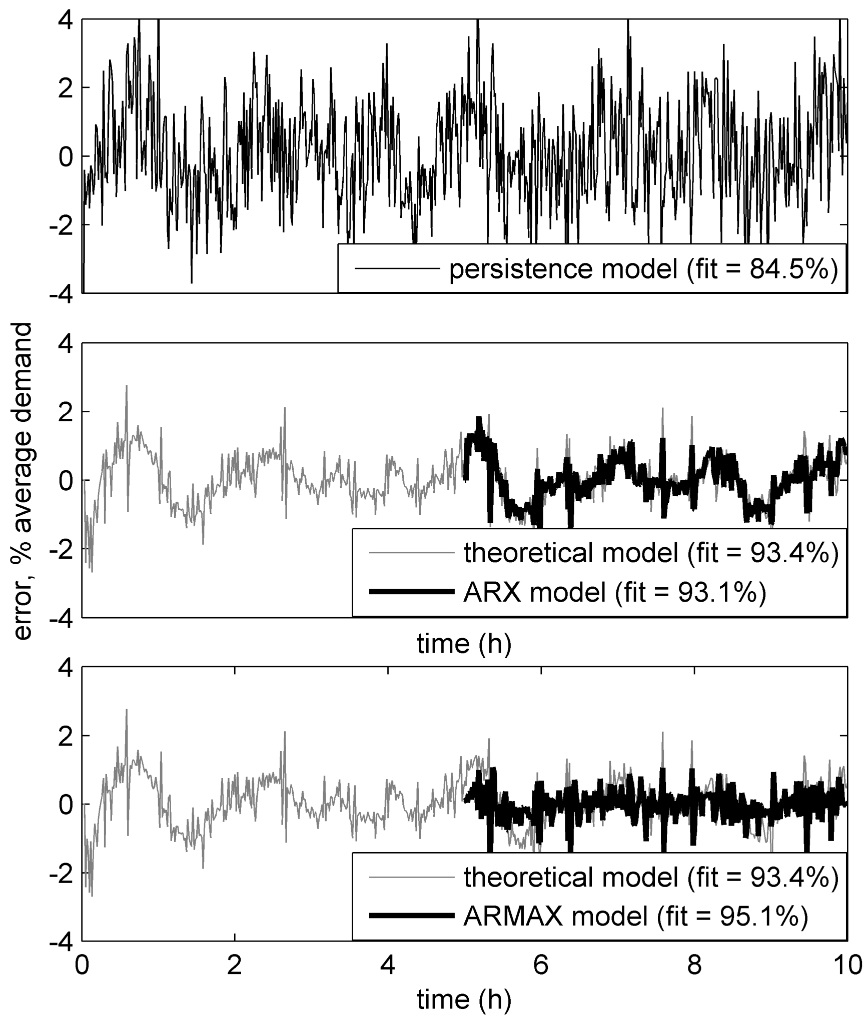
- Stochastic input signal:

$$u_{t_n} = \sum_{i=1}^{M} v_{n+i}$$

$$v_n = N\left(0, \sigma_v\right)$$

$$M = 25,\ \sigma_v = 5\times 10^{-3}$$

- Time series parameters can be determined by prediction error minimization – *IF* y_{tn} can be measured



These figures show how various models predict demand variability subject to a stochastic input signal

Minimum variance controller

- Rearrange time series model

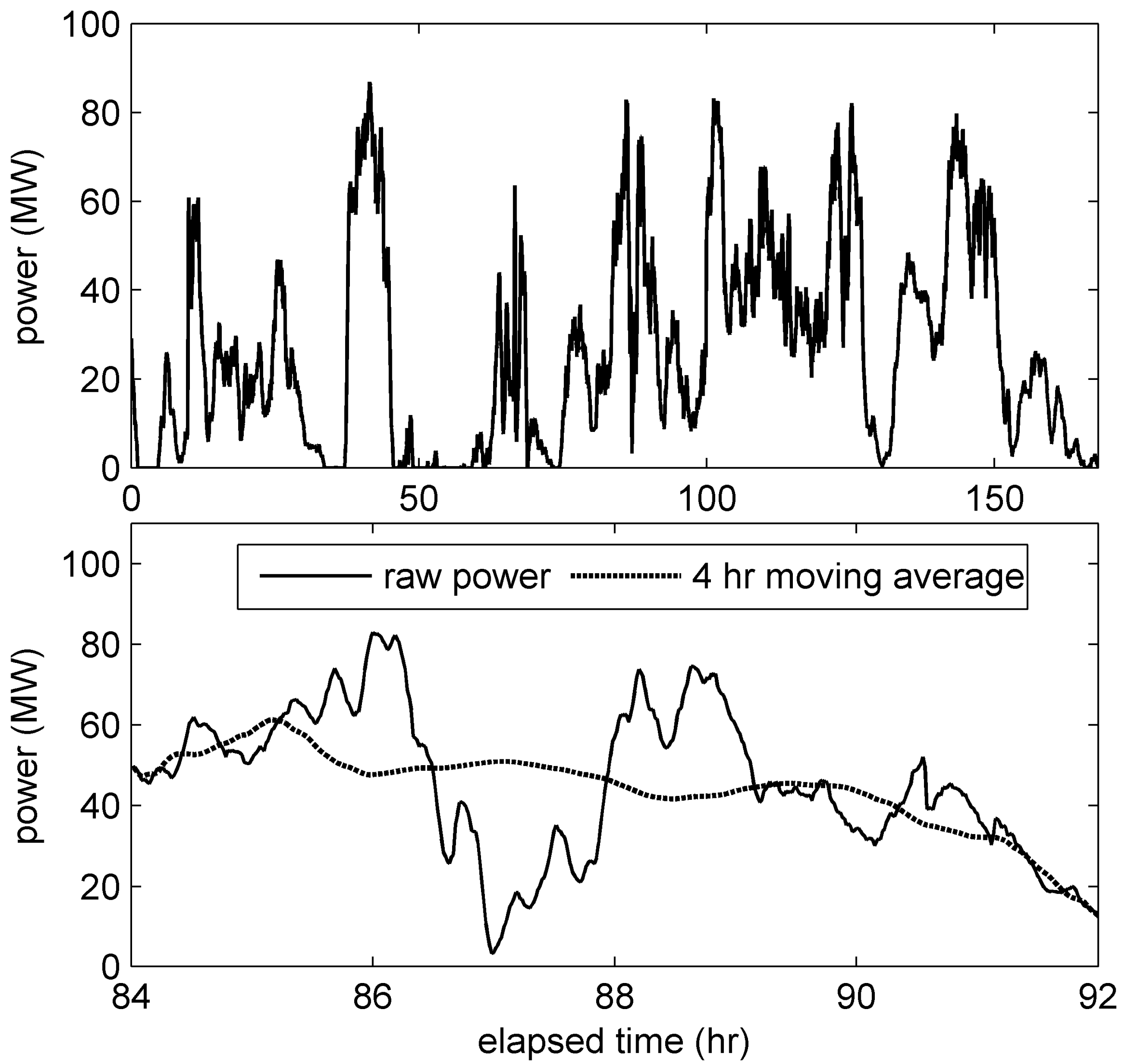
$$u(t_n) = \frac{C(q)\, y^m(t_{n+1}) - \dfrac{C(q) - A(q)}{q^{-1}}\, y(t_n)}{B(q)}$$

- $y^m(t_{n+1})$ is the reference output
- …assumes that one time step is required for the input signal to affect the output; use $y^m(t_n)$ if the input signal has an immediate effect.
- A, B, and C vectors can be determined by system identification or from theoretical parameterization

$$\Delta y_{t_{n+1}}^{ss} = -\frac{\Delta u_{t_n}}{\delta} \sum_i \frac{1}{\eta} P_i$$

Load Modeling and Control:

Variable output from renewables

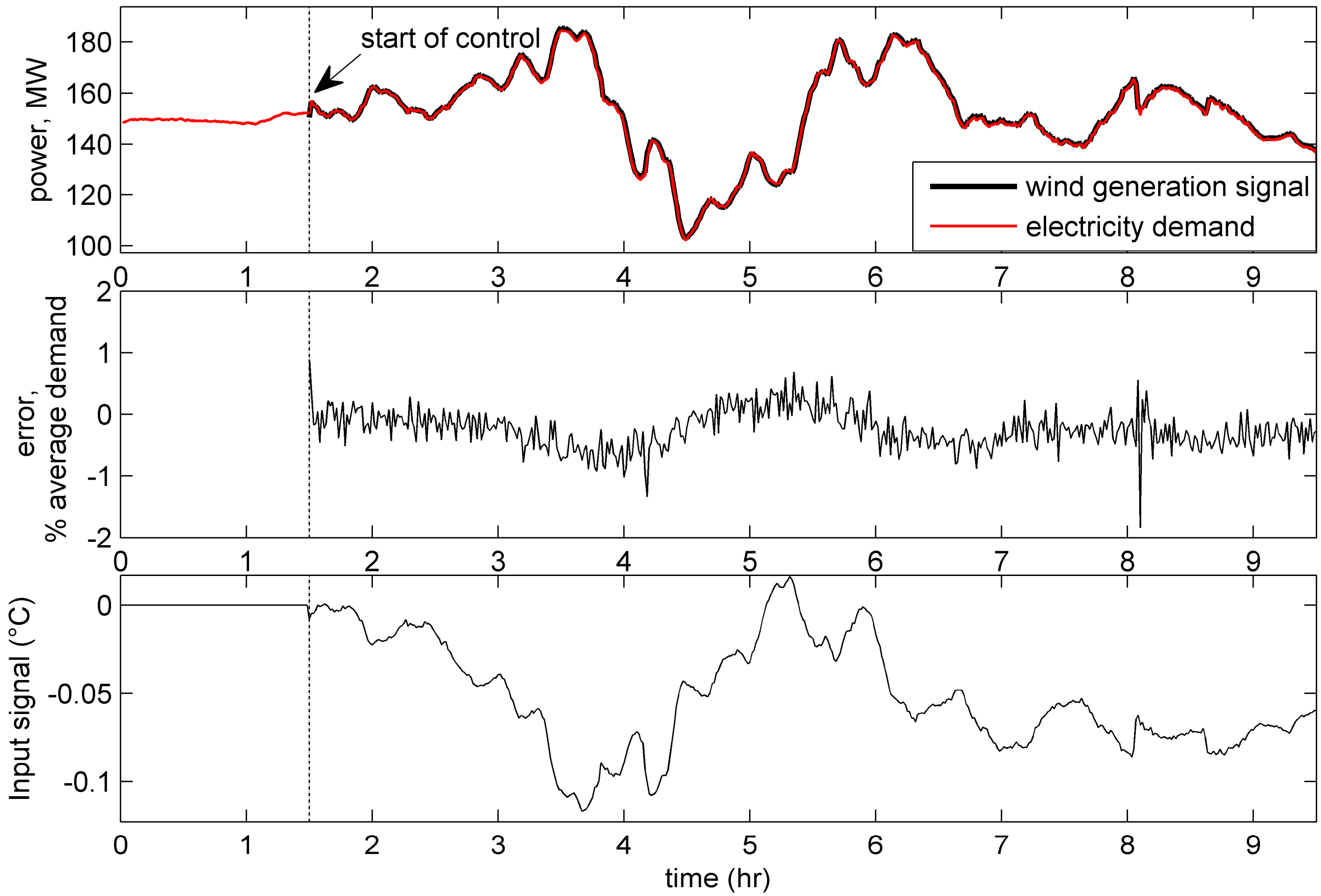


Smoothed output is easier for dispatchable generation to follow

Theoretical MVC Performance

Buffalo Ridge wind production matched to 60,000 TCLs

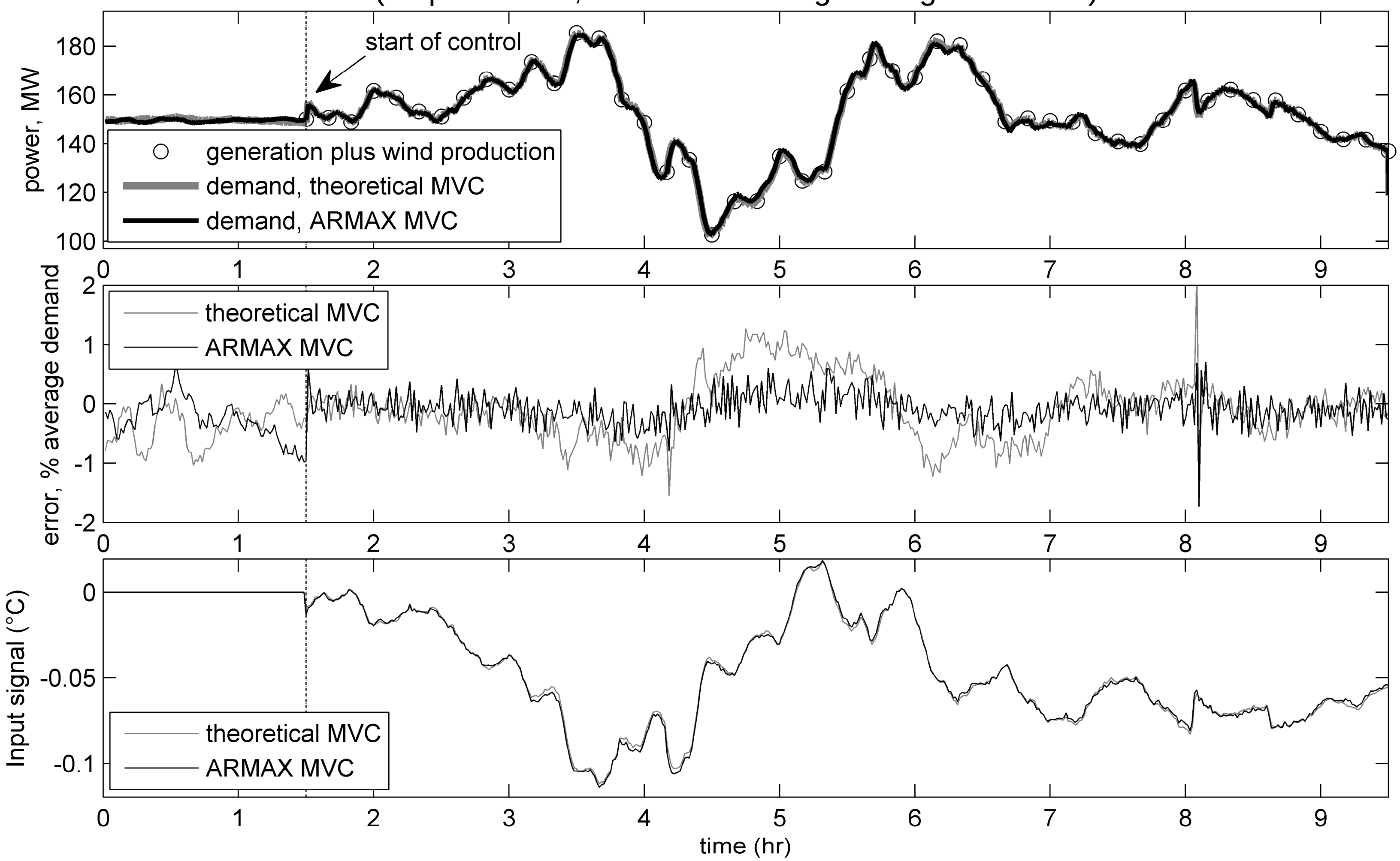
(output scaled, four hour moving average removed)



…and ARMAX MVC Performance

Buffalo Ridge wind production matched to 60,000 TCLs

(output scaled, four hour moving average removed)



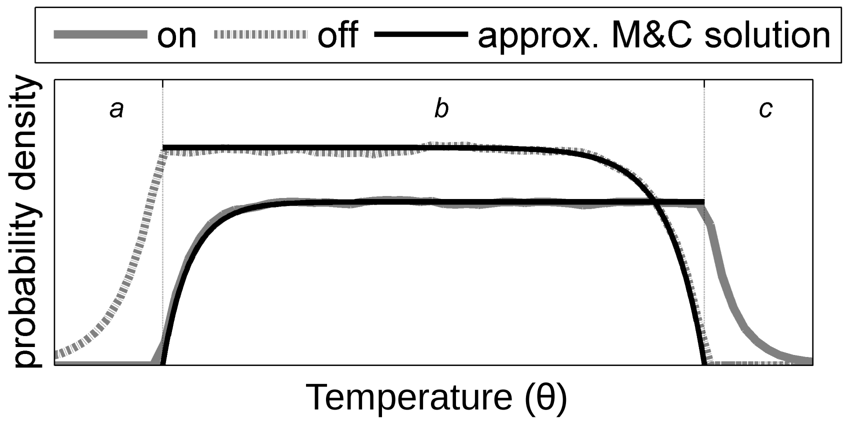
DR = storage?

- Simulation results show equivalent to 30MWh battery
- Per load, performance is 0.5kWh of energy capacity and 0.75kW of power capacity
- Performance dependent on quality of controller
  - Limiting factor is stability of feedback loop

Can we identify load characteristics that will improve performance?

- Need a measure of how quickly disturbances decay

Fokker-Planck Approximation



$$\frac{\partial f_0}{\partial t} = \frac{\partial}{\partial \theta}\left[\left(\frac{1}{CR}\left(\theta\left(t\right)-\theta_a\right)\right) f_0\right] + \frac{\sigma^2}{2}\frac{\partial^2}{\partial \theta^2} f_0$$

$$\frac{\partial f_1}{\partial t} = \frac{\partial}{\partial \theta}\left[\left(\frac{1}{CR}\left(\theta\left(t\right)-\theta_a\right)+\frac{P}{C}\right) f_1\right] + \frac{\sigma^2}{2}\frac{\partial^2}{\partial \theta^2} f_1$$

- Coupled by B.C. at deadband limits
- Original formulation due to Malhamé & Chong, 1985
- Assumes parameter homogeneity
- M&C found stationary sol'n with $\theta(t) - \theta_a$ constant

Fokker-Planck Approximation, ctd

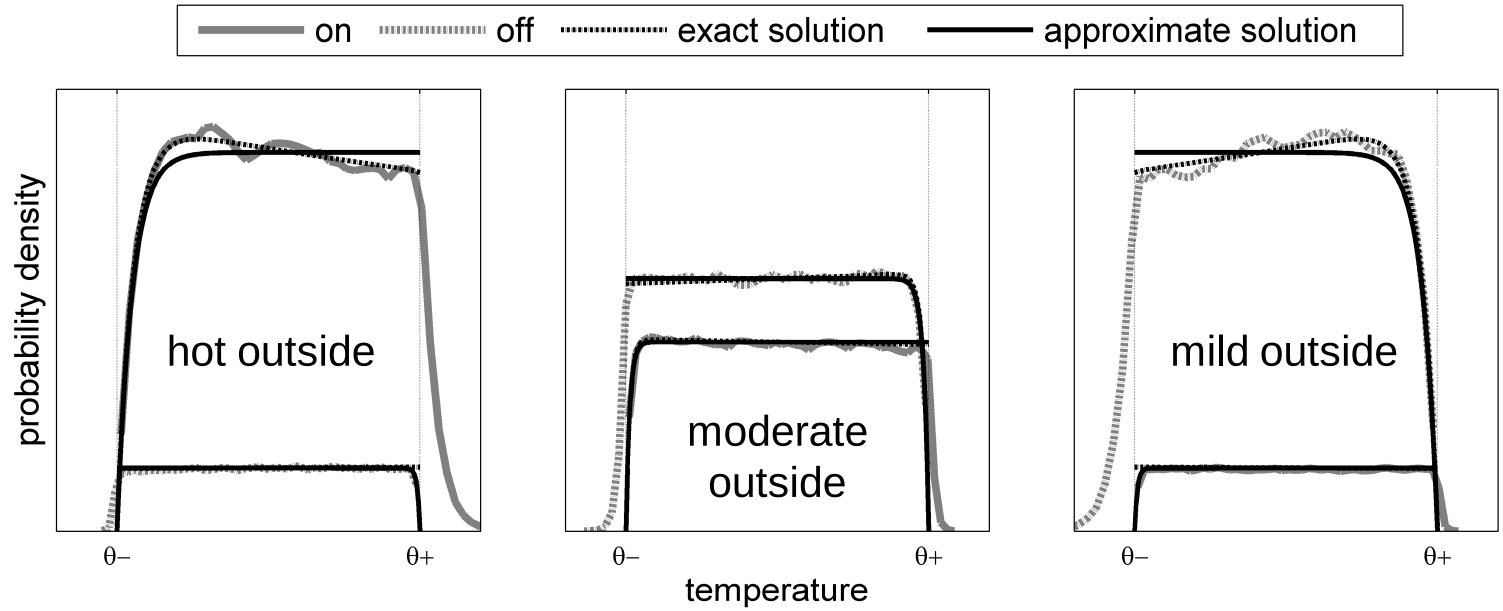
- Non-stationary solution eigenvalues will determine how quickly disturbances decay to steady state.
  - …unable to find nonstationary solutions under M&C assumption

- However, the original system can in fact be solved by separation of variables ($f\left(\theta,t\right)=\varphi\left(\theta\right)e^{-\lambda t}$) and the series method. The result:

$$\varphi = a_0 e^{-\xi^2}{}_1F_1\left(-\frac{\lambda CR}{2};\frac{1}{2};\xi^2\right)+a_1\xi e^{-\xi^2}{}_1F_1\left(-\frac{\lambda CR-1}{2};\frac{3}{2};\xi^2\right)$$

${}_1F_1$ is the confluent hypergeometric function of the first kind and ξ is a state-dependent transformation of θ.

Fokker-Planck Solution

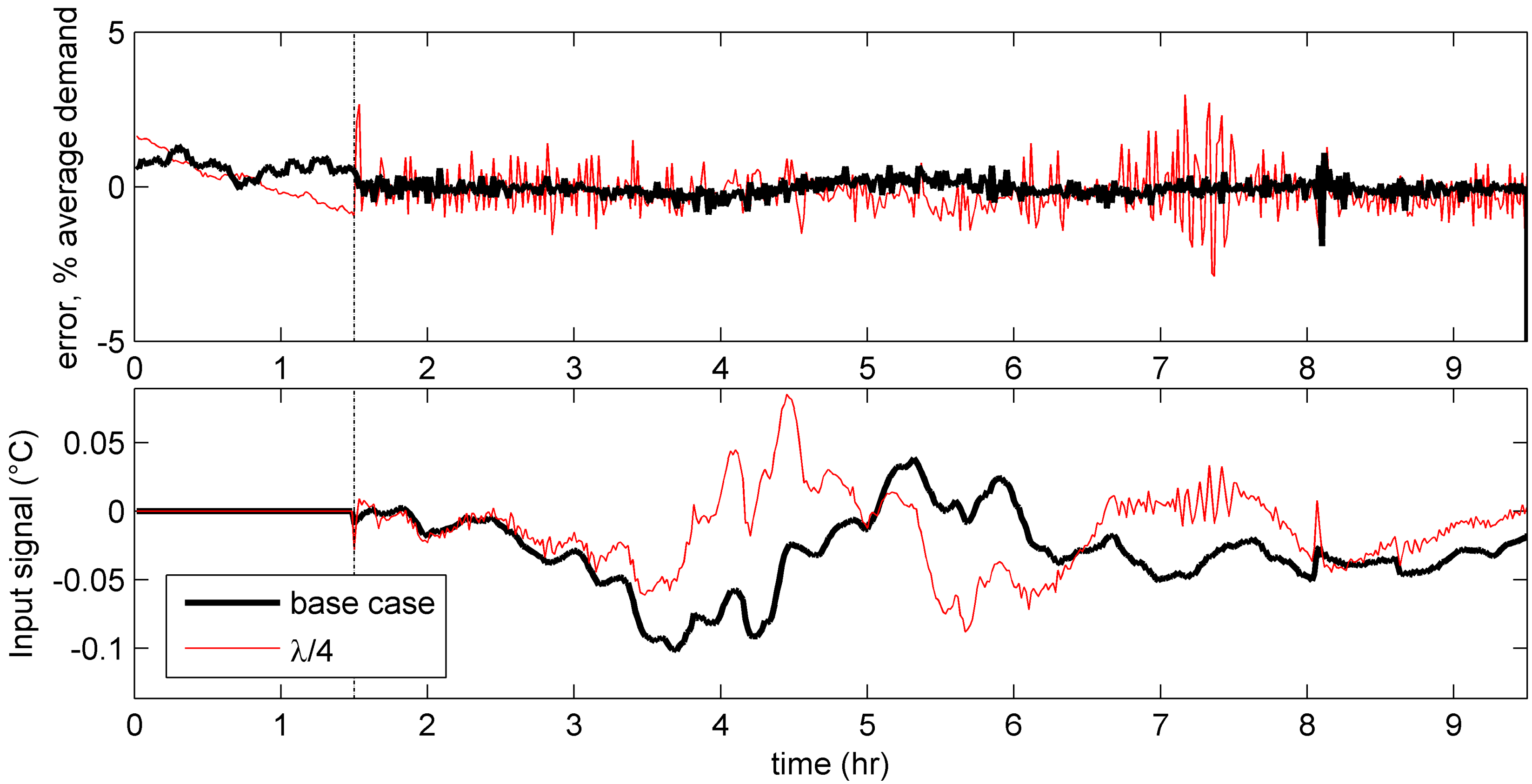


- Although the hypergeometric functions are not very intuitive, the eigenvalues are:

$$\lambda_k = \frac{k}{CR}, \quad k = 0, 1, 2, \ldots$$

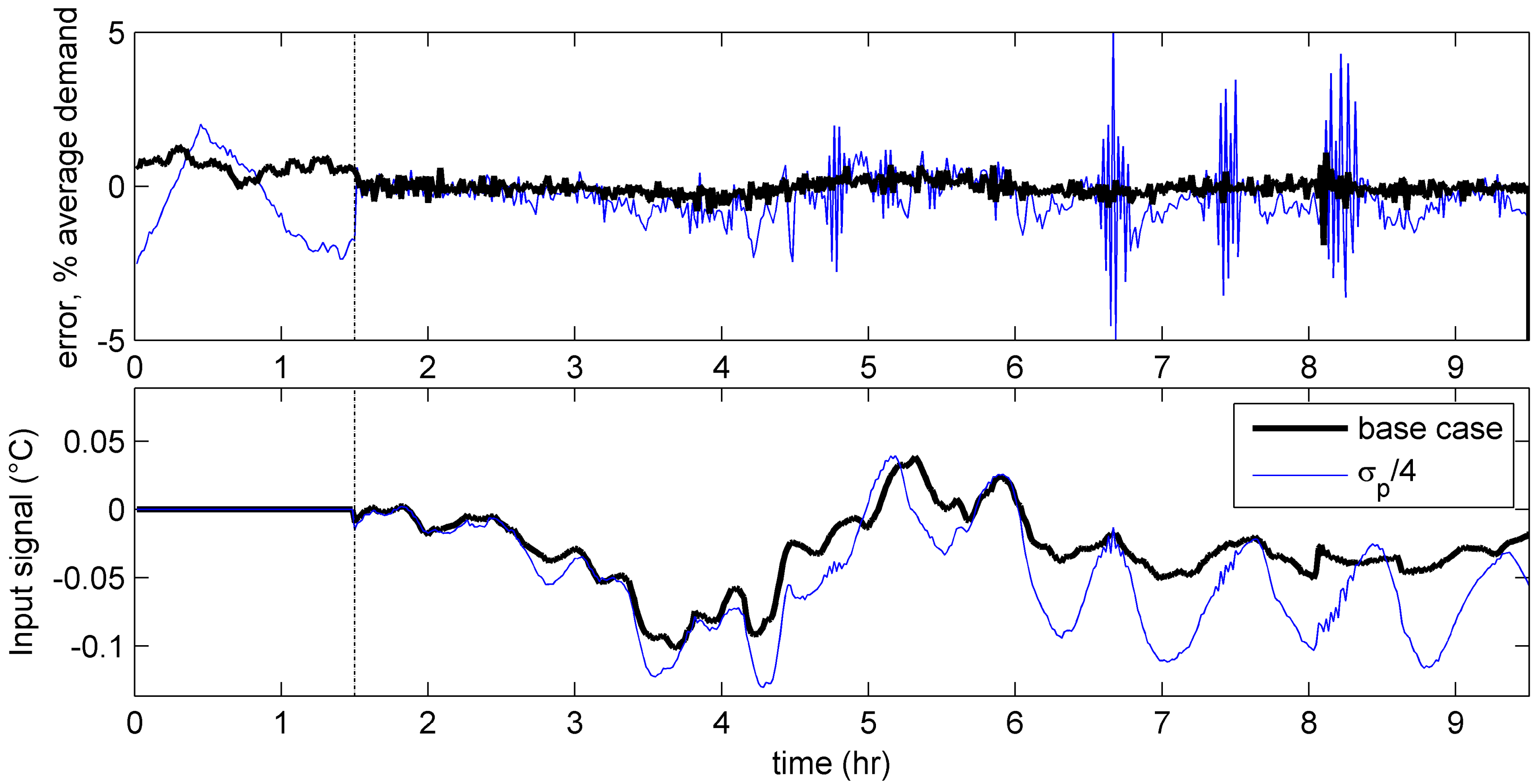
- CR is the building thermal constant → smaller CR, faster transient decay

MVC performance for different load characteristics – smaller eigenvalue



- RMSE, original parameters = 0.25
- RMSE, 4x smaller eigenvalue = 0.75

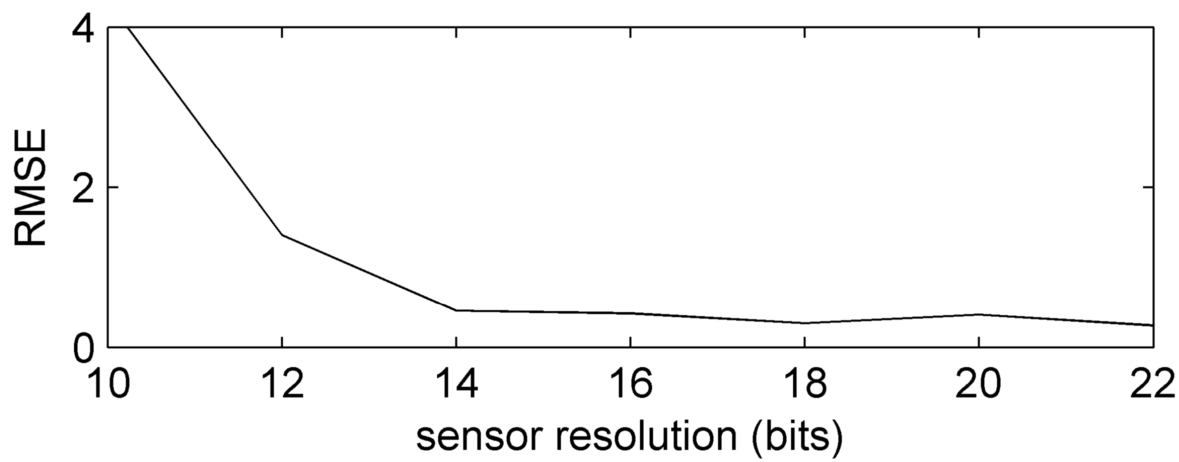
MVC performance for different load characteristics – less heterogeneity



- RMSE, original parameters = 0.25
- RMSE, 4x smaller parameter s.d. = 0.98

What about thermostat resolution?

- Previous results were for infinitely adjustable thermostats
- Figure below shows result when temperature is sensed with the indicated resolution



- 14 bit resolution sensors are available and inexpensive

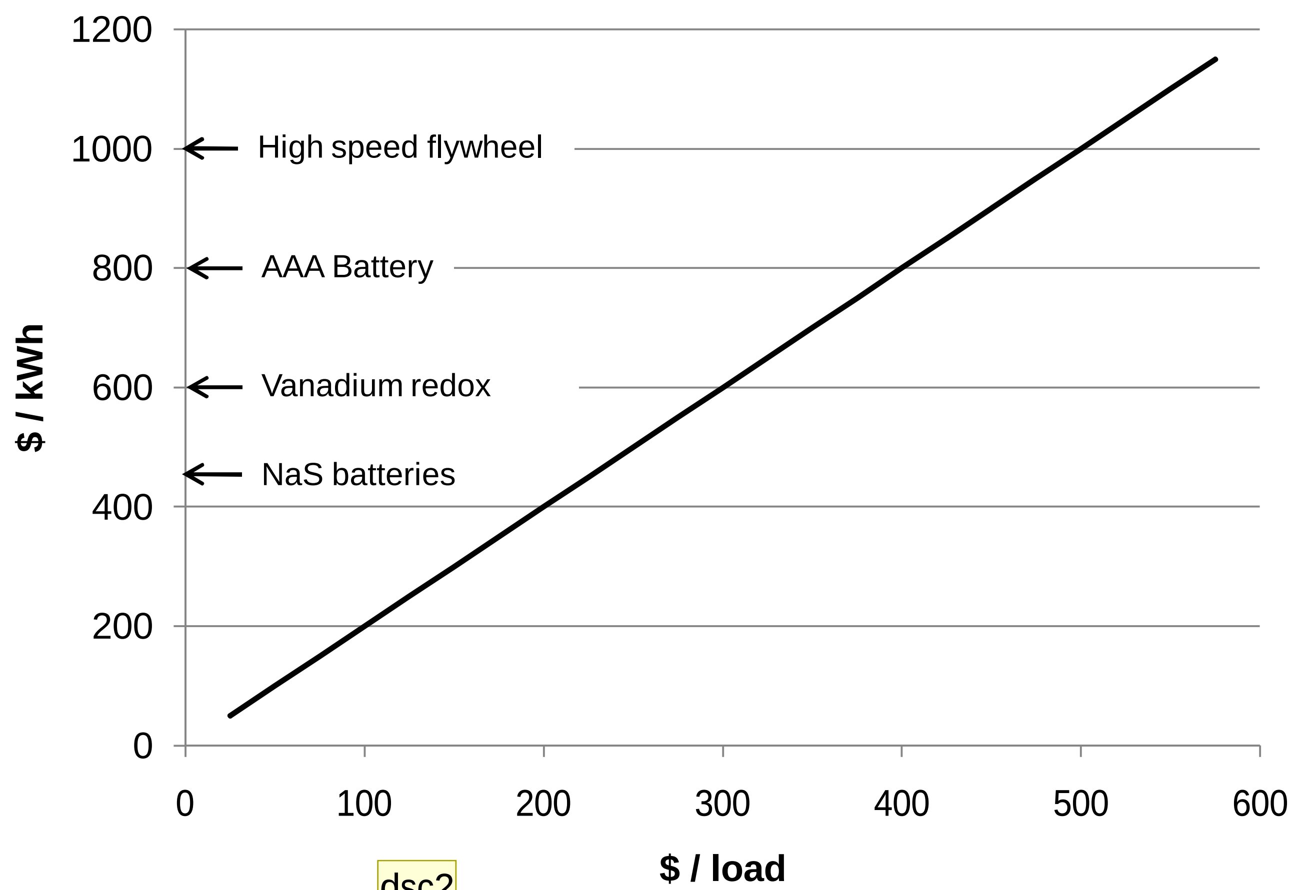
Storage cost comparison

Simulations showed approximately ~30MWh of storage.

$/kWh example :

- 800 AAA batteries store 1 kWh.
- At about $1 per battery, that's $800/kWh
- You'd need 400 batteries in each home to get the same response

Effective cost of loads as energy storage devices



Alternative technology estimates from "Solar Energy Grid Integration Systems –Energy Storage (SEGIS-ES)," Sandia National Lab Report SAND2008-4247

dsc2

Slide 26

dsc2 would be even less expensive if consumers were willing to feel some discomfort…

Duncan Callaway, 1/26/2009

Summary

- Load synchronization produces large response
- Linear approximation performs well
- Eigenvalue is a function of thermal time constant
  - Controller performance is better with less thermal mass, less insulation in buildings
  - (but of course there is less total “storage” capacity)
- System diversity improves performance
- TCLs can provide services in regulation and load following time scales without affecting comfort

Open questions and current work

- Identification of output signal from total system demand
- Better thermal load models (heterogeneity)
- Examine other loads (e.g. water heating, refrigeration) and quantify potential
- Can we use a load switch to get reductions *and increases* in demand?

Open questions and future work…

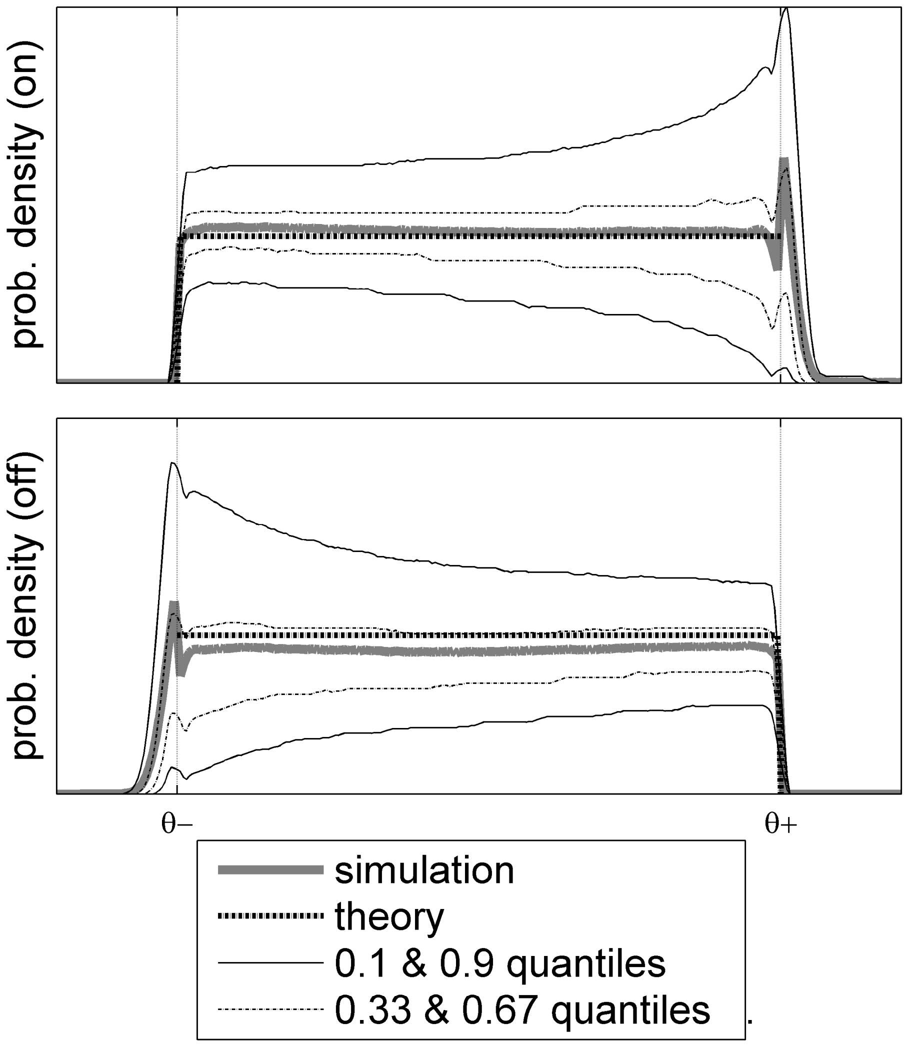
- Control strategies –
  - distributed / decentralized
  - model predictive control
- Integration with power system simulations Ongoing research funded by California Energy Commission
- Collaboration with CA ISO to direct research

Additional Slides

Table 1: Model parameter values

Parameter	Value
R, Average thermal resistance	2 °C/kW
C, Average thermal capacitance, unless noted otherwise	10 kWh/°C
P, Average energy transfer rate	14 kW
η, Load efficiency	2.5
θ_s, Temperature set point	20°C
δ, Thermostat deadband	0.5°C
θ_a, Ambient temperature, unless noted otherwise	32°C
σ, Noise standard deviation, unless noted otherwise	0.01°C $s^{-1/2}$
σ_p, *Standard deviation of lognormal distributions, as a fraction of the mean value, for* R, C, *and* P, *unless noted otherwise*	0.2

“Static” picture of disturbance rejection



Stochastic input signal:

$$u_{t_n} = \sum_{i=1}^{M} v_{n+i}$$

$$v_n = N\left(0, \sigma_v\right)$$

$$M = 25,\ \sigma_v = 5\times10^{-3}$$

Quantiles converge as they approach the deadband limit

Linear Approximation: One Step Ahead Model Performance

$$u_{t_n} = \sum_{i=1}^{M} v_{n+i}$$

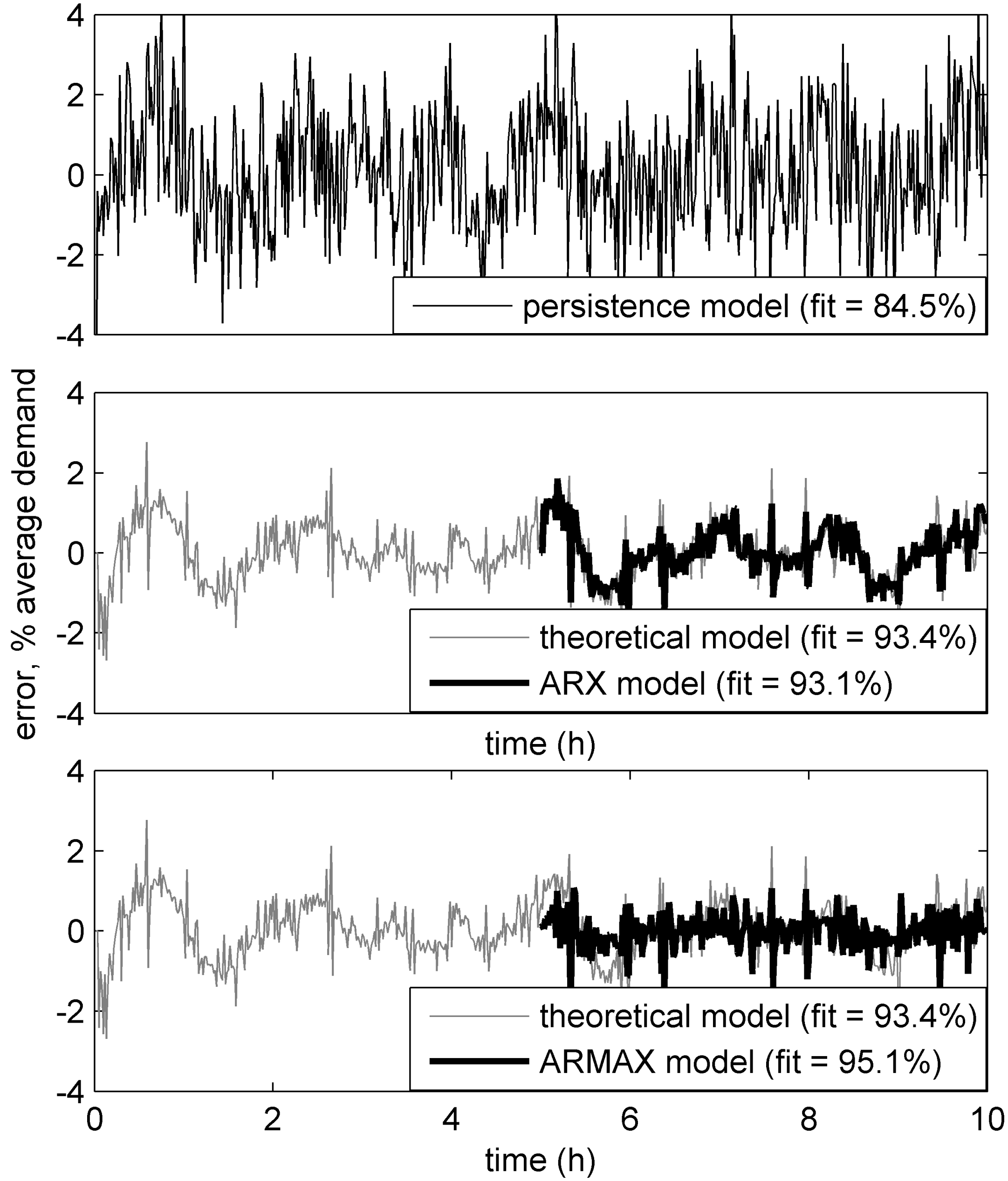
$$v_n = N\left(0, \sigma_v\right)$$

$$M = 25,\ \sigma_v = 5\times10^{-3}$$

Fit is measured as

$$\left(1 - \left\|\hat{y}_t - y_t\right\|\right) / \left\|\bar{y} - y_t\right\|$$

$\|\cdot\|$ is the Euclidean Norm.



Back of the envelope…

- Simulations showed average load of 140MW, with ±40 MW of fluctuation
- Consider two operation scenarios:
  1. Run 100 MW baseload plant at constant output and combustion turbine (CT) to manage fluctuations, average 40 MW
  2. Run 140 MW baseload plant at constant output and use TCLs to manage fluctuations
- Consider two generation scenarios:
  A. ‘baseload’ is coal
  B. ‘baseload’ is combined cycle gas turbine (CCGT)
- Assume:
  - coal (base load) = $0.015/kWh, 1.9 lbs CO_2/kWh
  - gas (combined cycle) = $0.05/kWh, 0.84 lbs CO_2/kWh
  - gas (simple cycle) = $0.075/kWh, 1.27 lbs CO_2/kWh

Back of the envelope…CTD

Baseload = coal		Baseload = gas	
Change in CO_2	Change in cost	Change in CO_2	Change in cost
+11%	-50%	-13%	-13%

Caveats:

- In practice, a mixture of generators will be used to follow fluctuations → Full system dispatch model needed to evaluate the approach
- Cooling loads not always available (others e.g. water heaters might be).
- Wind fluctuations from one plant will be partly counteracted by natural fluctuations in load or from other wind plants
- But if PCTs or AMI are being installed for other reasons, this is a “free” resource