Demand Response: Architecture, Privacy and Economics for Integrating Stochastic Renewables

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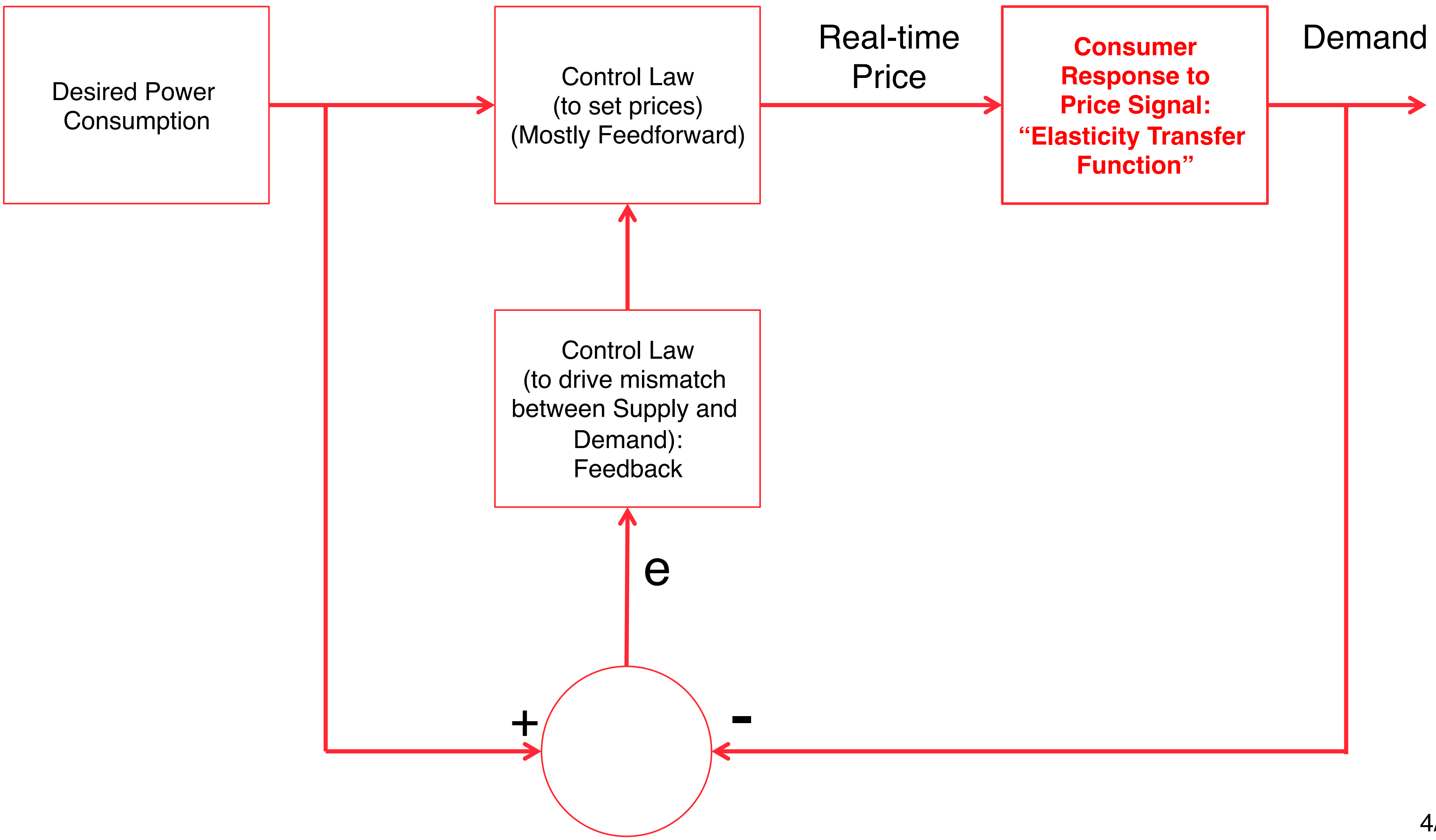
Towards a theory for understanding demand response: Some vignettes

- Modeling demand response as a dynamic system
- Price mediated stochastic optimal control
- Architecture for demand response with inertial thermal loads
- PMUs: From Big Data to low dimension
- Optimal operation of EV Charging Stations

Modeling demand response as a dynamic system

Investigating architecture …



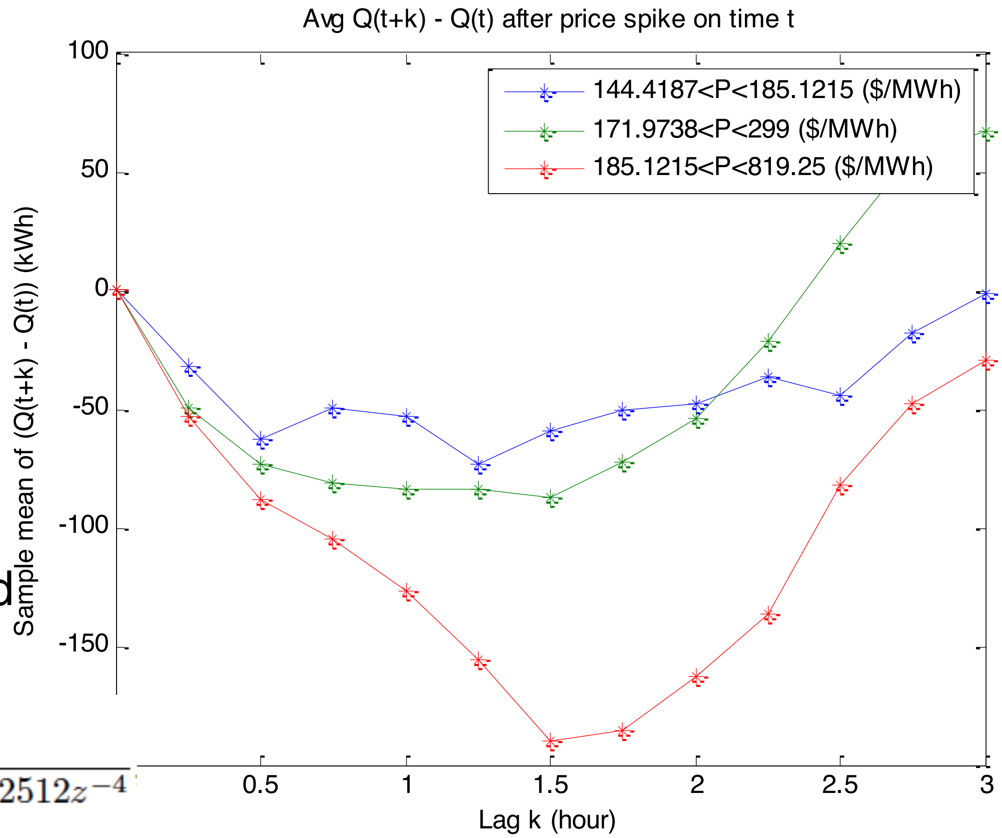
Demand response as a dynamic system

- Motivation: Close price loop around demand response
  - Data obtained from commercial and industrial loads in Texas
  - Model price responsive demand
- Differentiated response: Difference between moderate vs high prices
- Moderate prices – ARX model

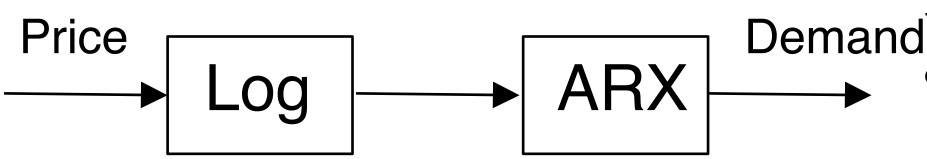
$$TF_{\text{Low}} = \frac{-0.8555z^{-1} + 0.5273z^{-2}}{1 - 0.8127z^{-1} - 0.0461z^{-3} - 0.0366z^{-5}}.$$

Demand response as a dynamic system: High prices

- More than 95th percentile of price = \$144 \$/MWh
  - High price rarely persists
  - Only 15 min spike
  - “Impulse response”



- Hammerstein system

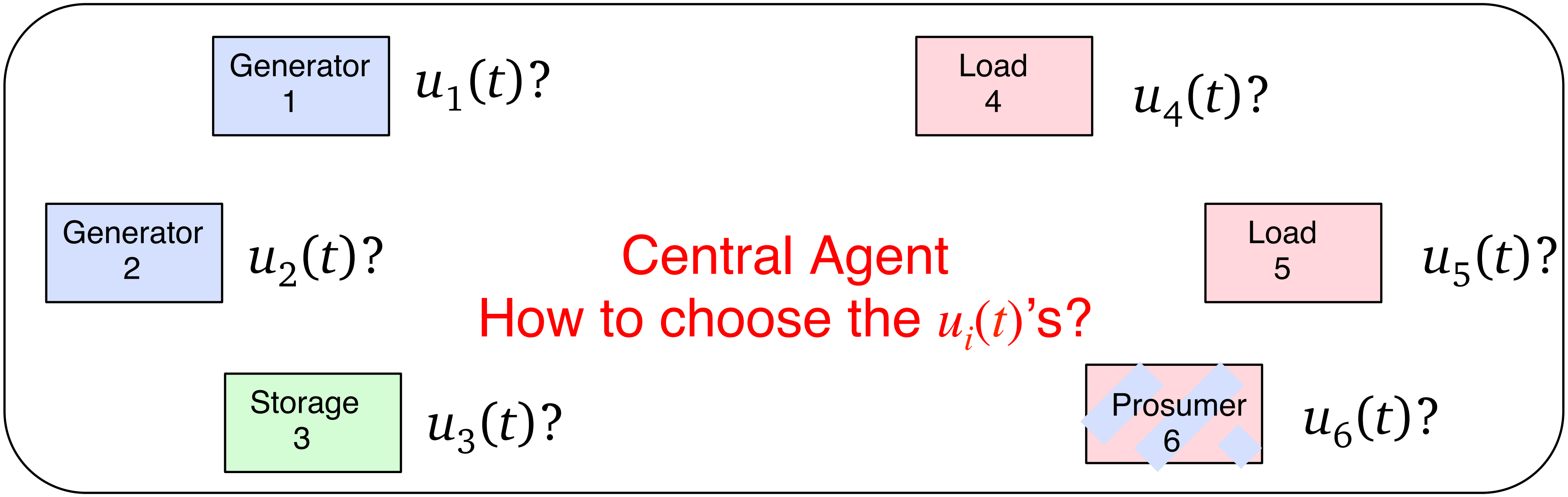


$$TF_{\text{Peak}}^{2:15pm} = \frac{-220.1z^{-4}}{1 - 0.4015z^{-1} + 0.2383z^{-2} - 0.2512z^{-4}}$$

J. An, P. R. Kumar and Le Xie, “On Transfer Function Modeling of Price Responsive Demand: An Empirical Study,” To appear in 2015 IEEE Power & Energy Society General Meeting, Denver, July 26--30, 2015.

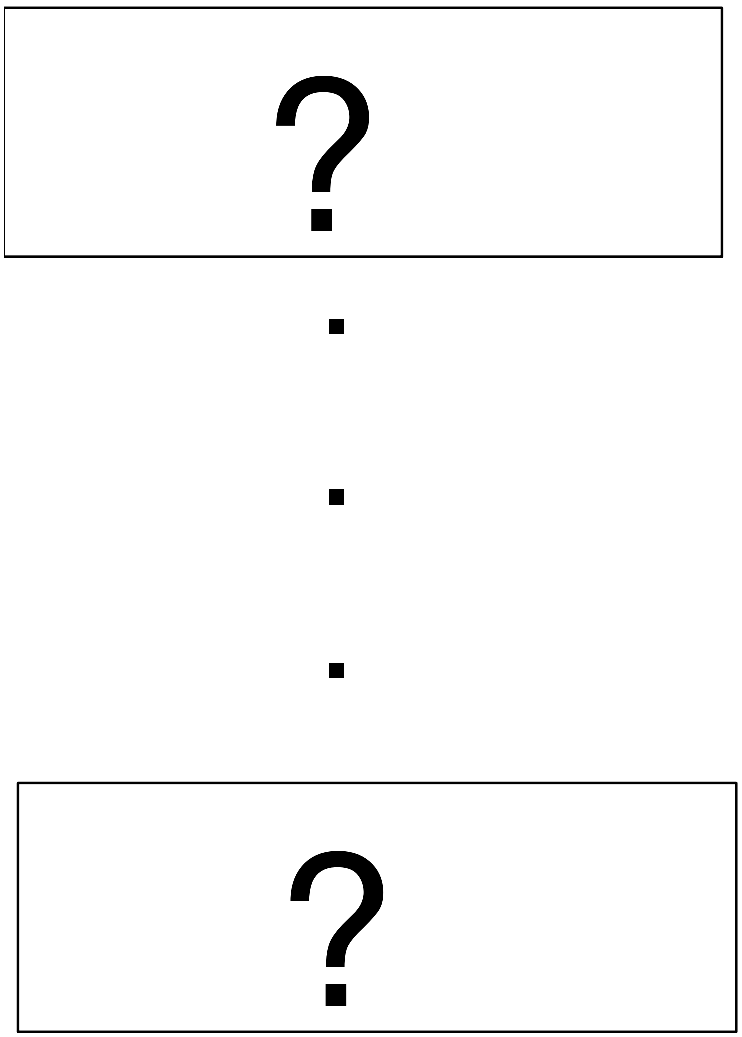
Price mediated stochastic optimal control

How to optimize a decentralized stochastic system?



- Dynamic constraints: Ramping rates, delays, nonlinearities, ARX models, max charging rate, etc
- How to arrive at an optimal control solution when there are many *generators, loads, prosumers, storage,* all with *dynamic constraints*?
- Fundamental difficulty: Witsenhausen problem
  - Optimal solution is generally intractable
  - We don't even know the systems involved

Model



- The mathematical problem of Central Agent
- Maintain balance

$$\sum_{n=1}^{N} u_n(t) = 0 \text{ for all } t = 1,2,\ldots,T$$

- Maximize total utility

$$Max \sum_{t=1}^{T} F_N(x_N(t))$$

- *Without* the Central Agent knowing anything about any individual Agent's dynamics or constraints or utilities or states, etc

Price mediation and iteration

- Central Agent announces prices $p(0), p(1), \ldots, p(\mathrm{T})$
- Each Agent n maximizes its own dynamic response

$$\underset{u_n(1),\ldots u_n(T)}{Max} \sum_{t=1}^{T} \left(F_n(x_n(t)) - p(t)u_n(t) \right)$$

- Central Agent iterates the price sequence

$$p(t)_{k+1} = p(t)_k - \alpha \sum_{n=1}^{N} u_n(t) \ \text{ for } t = 0,1,2,\ldots,T-1$$

for $k=1,2,\ldots$, until it converges

Optimality results

- Deterministic system
  - Converges under some convexity assumptions
  - Solution it arrives at is optimal
- Stochastic system
  - Repeat the iteration process at each time instant
    - A la model predictive control
    - But proceed to convergence
  - Then converges to optimal solution for some systems:
  - For systems with common information about uncertainty
  - Even for some systems with independent information
  - But challenging for correlated information

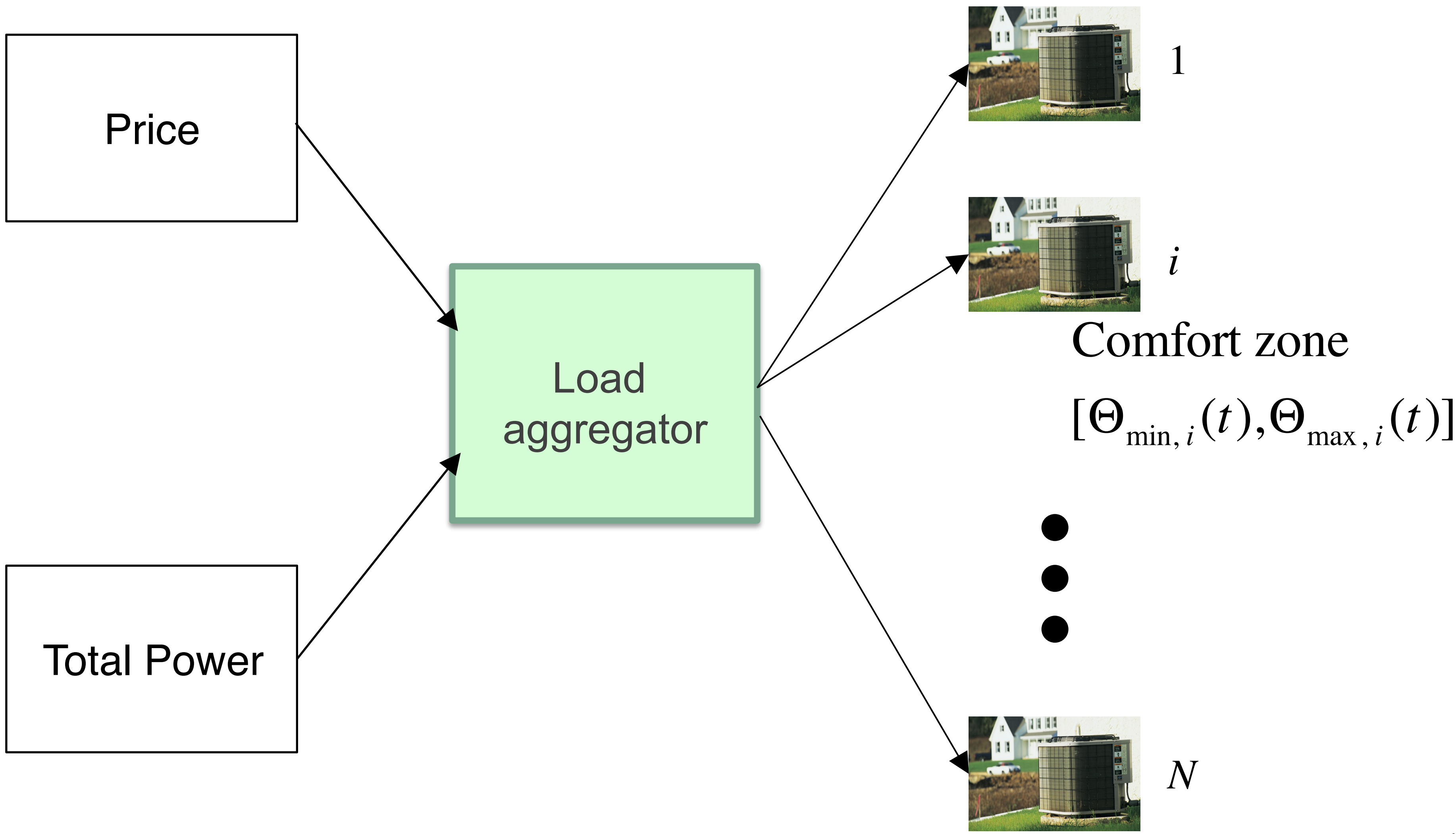
Rahul Singh, Ke Ma, Anupam A. Thatte, P. R. Kumar and Le Xie, ``A Theory for the Economic Operation of a Smart Grid with Stochastic Renewables, Demand Response and Storage.'' Submitted to Proceedings of 54th IEEE Conference on Decision and Control, December 15--18, 2015, Osaka, Japan. (Invited Paper).

An architecture for demand response with inertial thermal loads

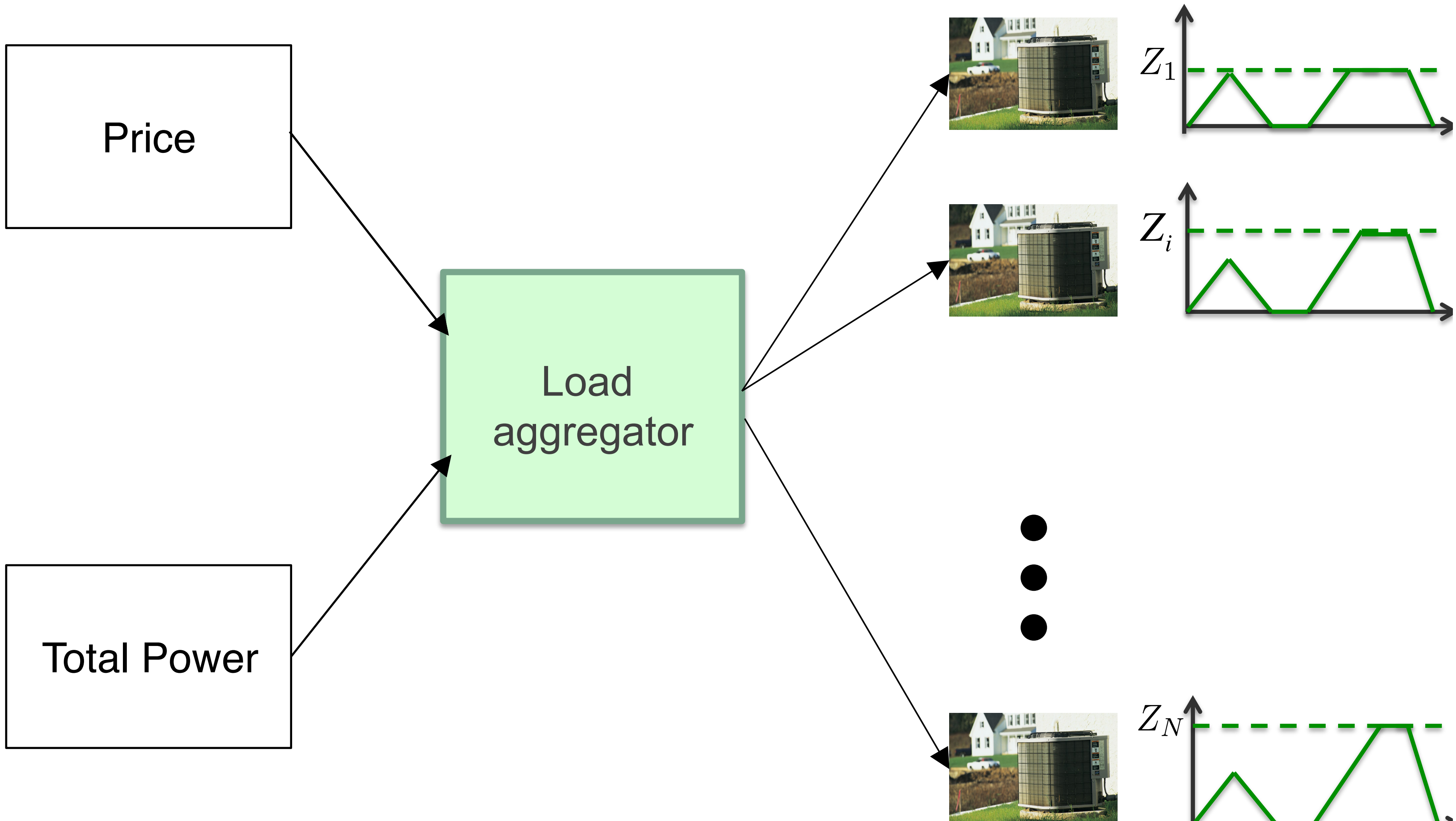
An Architecture for Demand Response

- Goals
  - Maximize utilization of renewable energy
  - Minimize variability of power required
  - Respect comfort constraints of homes
- Architecture
  - How to achieve demand *pooling*?
  - Respect privacy: No intrusive sensing
  - Minimize communication requirements
    - Volume and latency of data
- Solution
  - "Optimal" – efficient in some sense
  - Computationally tractable for large number of homes

Load aggregator

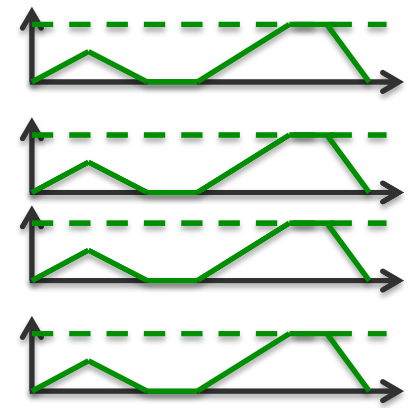


Thermostatic control with set points Z_i

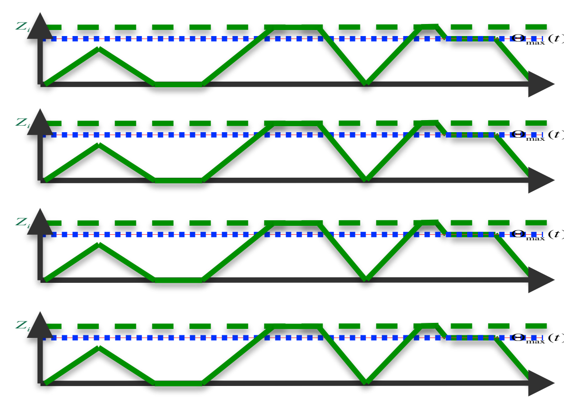


Problem: Synchronization of demand response

- Optimal solution: All users behave alike
- Loads synchronize and move in lock-step

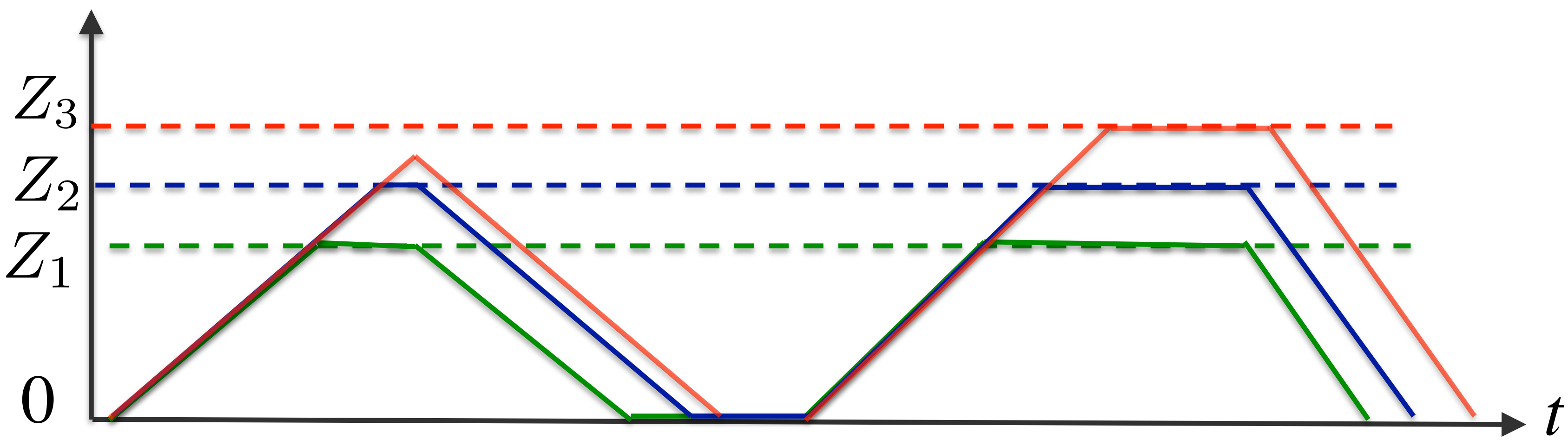


- Robustness problem: Suppose users change comfort level settings at same time
  - Super bowl Sundays @ game time
- Demand suddenly rises, causing large peak in nonrenewable power required
  - Model cost as $\lim_{T\to\infty} \frac{1}{T}\int_0^T \left(P^n(t)\right)^2 dt$



Staggered set-points

- De-synchronize load behaviors
- Choose different set-points $(Z_1, Z_2, ..., Z_N)$ for different loads



Stochastic optimization problem for $\{Z_1, Z_2, \ldots, Z_N\}$

- Stochastic wind process: $P^w(t)$
- Temperature dynamics: $\dot{x}_i(t) = h - P_i(t)$

  $P_i(t) = P_i^w(t) + P_i^n(t)$
- Comfort specification: $\dot{x}_i(t) \in [0, \Theta_{\max}(t)]$
- Robustness model: Stochastic process $\Theta_{\max}(t)$
- Set-point control: $P_i^n(t) = \begin{cases} h \text{ if } x_i(t) = Min(Z_i, \Theta_{\max}(t)) \\ 0 \text{ otherwise} \end{cases}$
- Cost: $C_N = \underbrace{\lim_{T \to \infty} \frac{1}{T} \int_0^T \left(P^n(t)\right)^2 dt}_{\text{Variation}} + \underbrace{\gamma_N \sum_{i=1}^{N} \left((x_i(t) - \Theta_{\max}(t))^+\right)^2 dt}_{\text{Discomfort}}$

The optimization problem for a finite number of loads

- Minimize

$$C^N(Z_1,\ldots,Z_N) = \sum(\text{Power level})^2 \times \text{Prob}(\text{Power level}) + \gamma_N \sum \text{Expected Discomfort}$$

- Subject to

$$0 \leq Z_1 \leq Z_2 \ldots \leq Z_N \leq \Theta_2$$

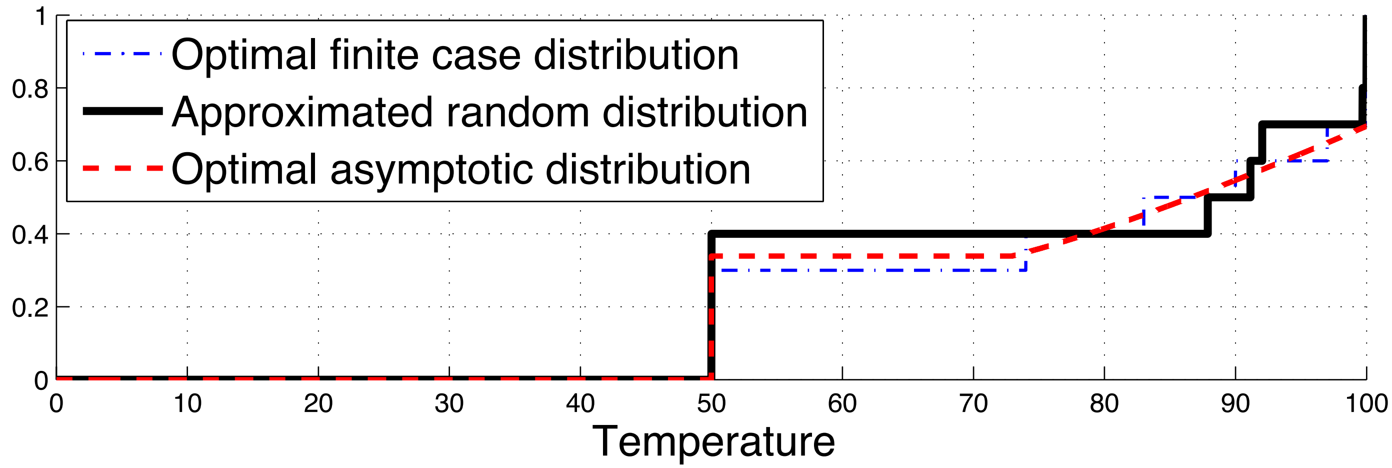
- Difficult
  - High dimensional when N is large
  - Complex
  - Need to solve different problems for different N's

Continuum limit as $N \to \infty$.

- Solution
  - Study asymptotic limit as $N \to \infty$.
  - Consider Set of loads = $[0,1]$
  - Can solve using analytical methods
    - Pontryagin Minimum Principle
  - Solution is explicit!
  - Also asymptotic solution is also nearly optimal even for small N!
  - Essentially this solves the problem for all N's

Solving for finite N: Approximation to continuum limit

- We can generate $\{Z_i\}_1^N$ according to continuum limit distribution, to approximate finite optimal distribution



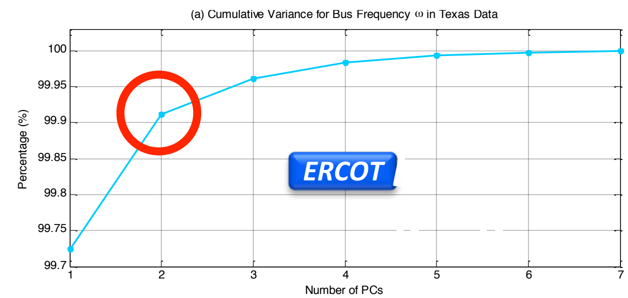
- Can be implemented in a privacy respecting manner
- Similar schemes to have different QoS contracts of users, with minimal knowledge

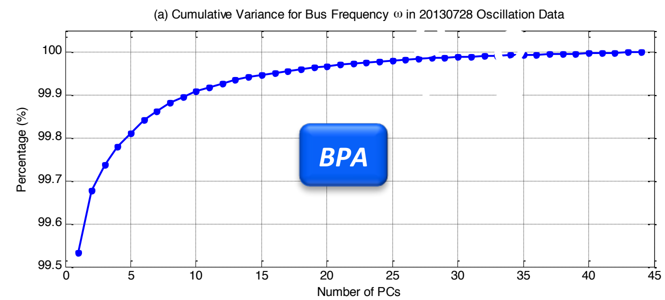
Gaurav Sharma, Le Xie and P. R. Kumar, "Large population optimal demand response for thermostatically controlled inertial loads." Proceedings of IEEE International Conference on Smart Grid Communications (IEEE SmartGridComm), pp. 259--264, October 21--24, 2013, Vancouver.

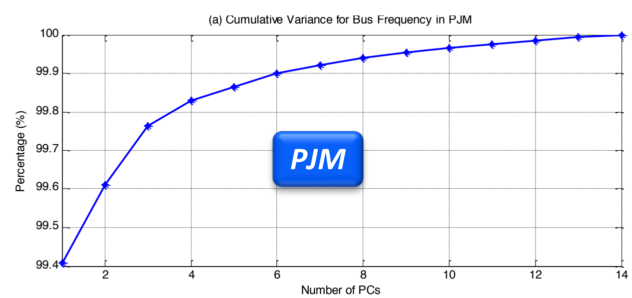
PMUs: From Big Data to low dimension and early event detection

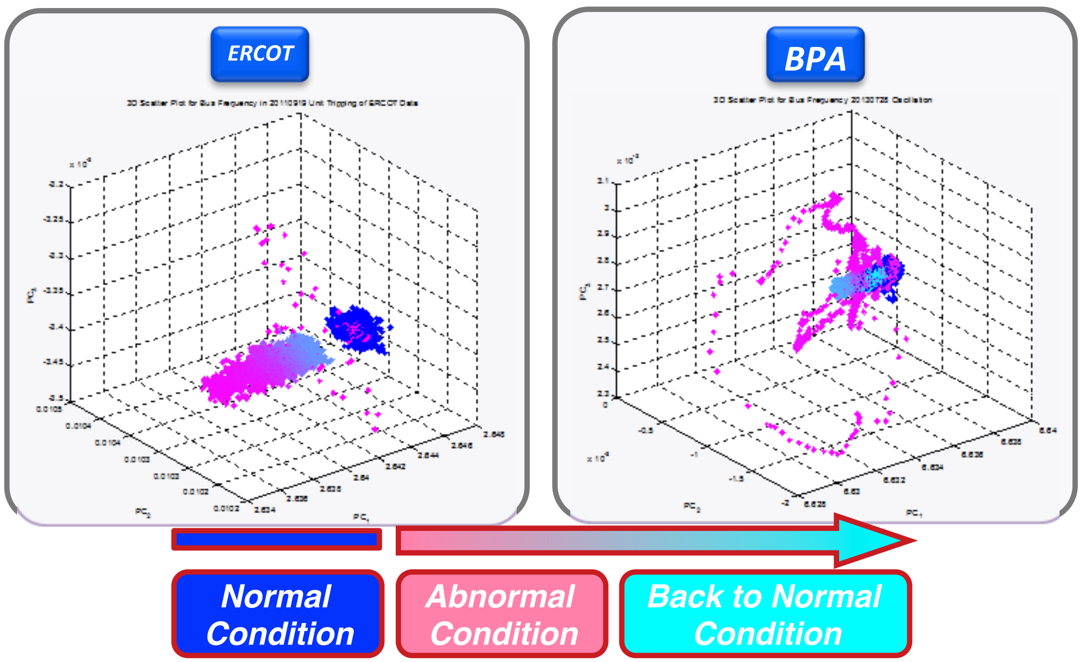
Integrating PMUs: Dimensionality reduction of big data for early event detection

- About 1000 PMUs in USA, 1700 in China
- TVAs 120 PMUs produce 36GB data per day
- Significant dimensionality reduction possible







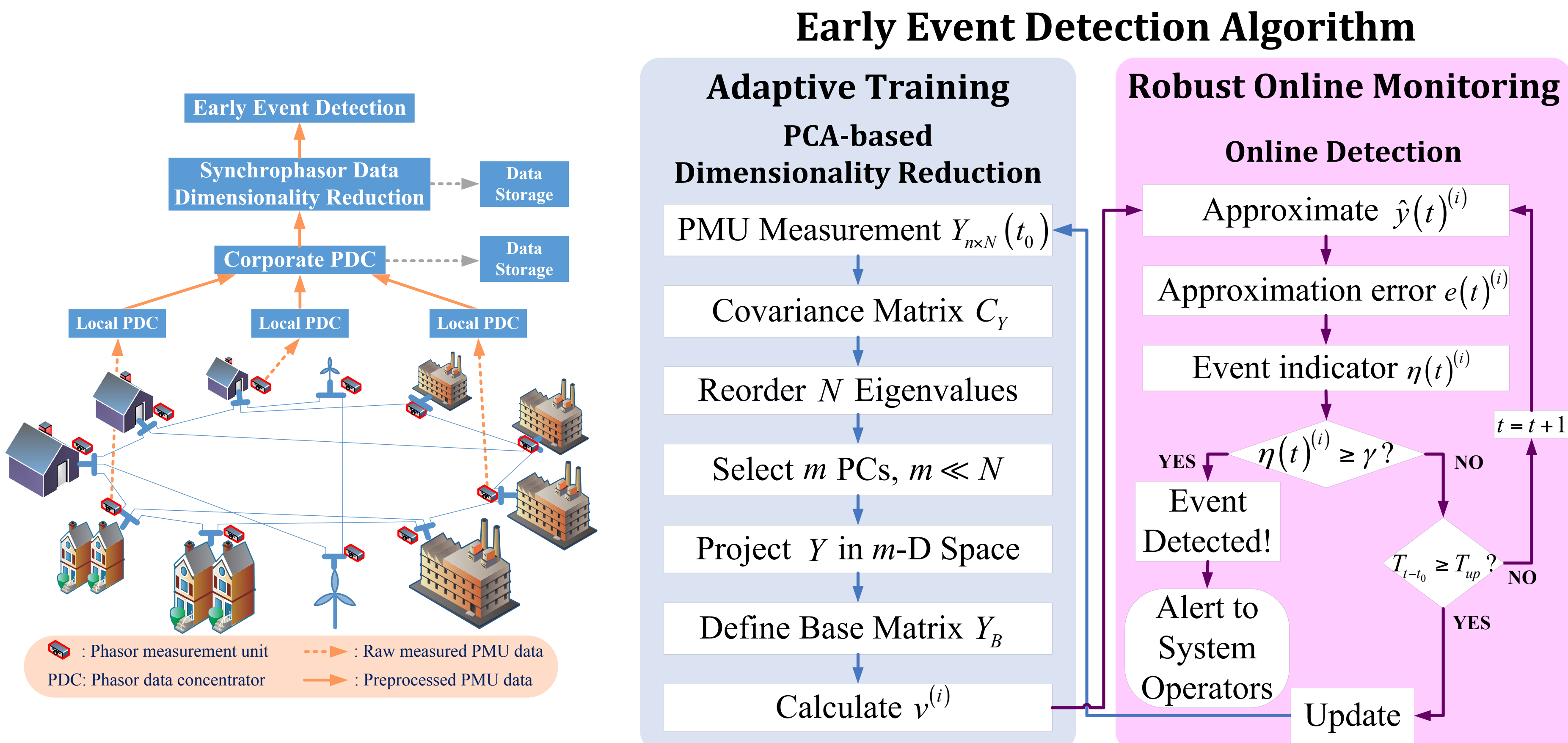


Bus Frequency in 20110919 Unit Tripping of ERCOT Data

3D Scatter Plot for Bus Frequency 20130728 Oscillation

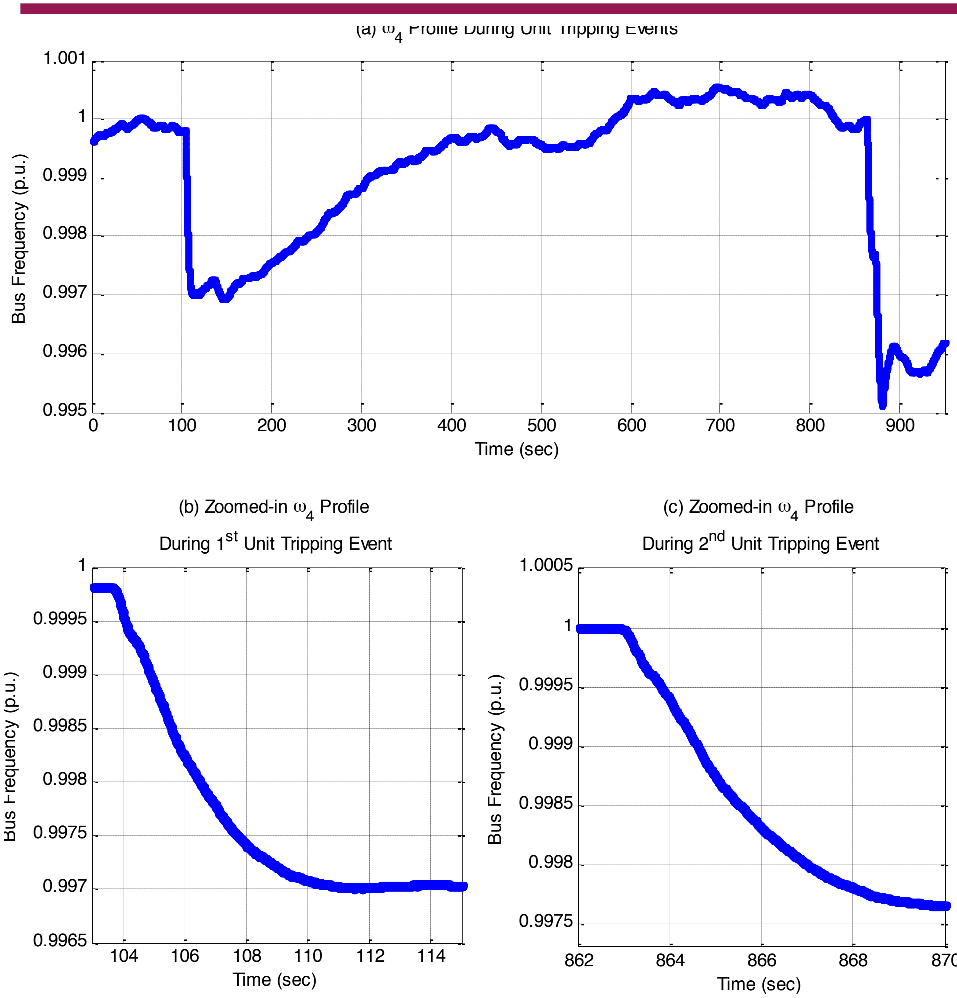
L. Xie, Y. Chen, P. R. Kumar, "Dimensionality reduction of synchrophasor data: linearized analysis and online applications," IEEE Trans. Power Systems

Early Event Detection Algorithm

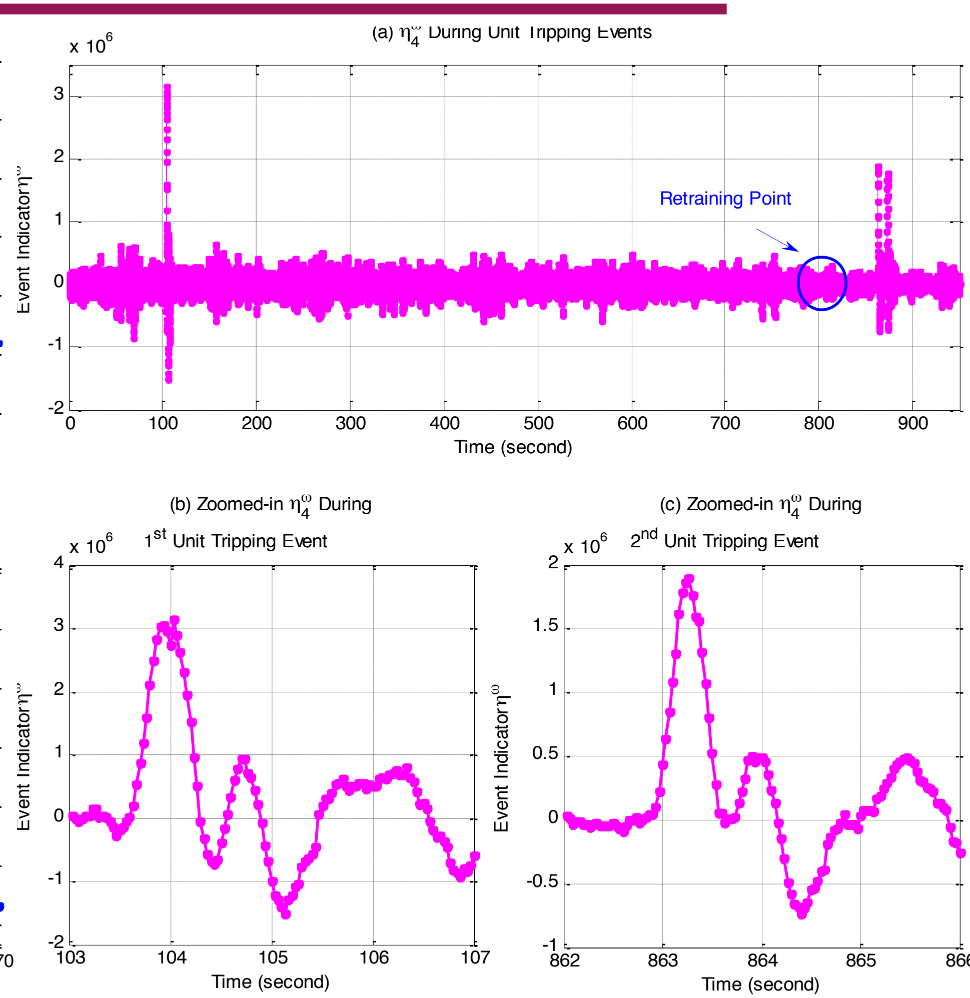


Yang Chen, Le Xie and P. R. Kumar, “Dimensionality Reduction and Event Early Detection Using Online Synchrophasor Data.” IEEE Power and Energy Society General Meeting (PES), pp. 1--5, Vancouver, British Columbia, Canada, July 21-25, 2013.

Case Study: Texas Unit Tripping



w4 profile.

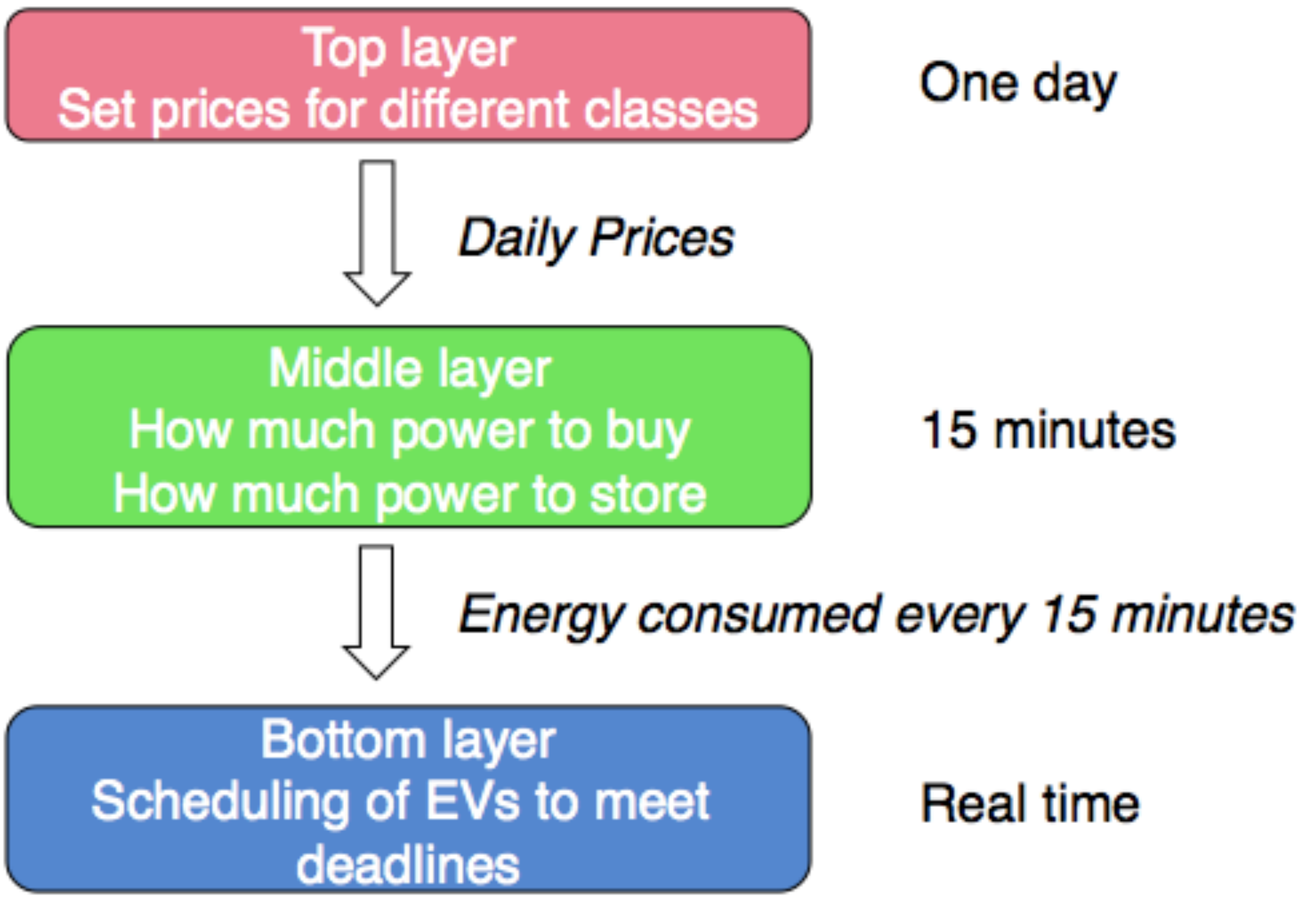


η_4^{ω} ***during unit tripping event.***

Yang Chen, Le Xie and P. R. Kumar, "Dimensionality Reduction and Event Early Detection Using Online Synchrophasor Data." IEEE Power and Energy Society General Meeting (PES), pp. 1--5, Vancouver, British Columbia, Canada, July 21-25, 2013.

Optimal operation of EV Charging Stations

EV Charging Stations: Layered Architecture Based on Time Scale Decomposition



Ke Ma, Le Xie and P. R. Kumar, “A Layered Architecture for EV Charging Stations Based on Time Scale Decomposition.” IEEE SmartGridComm, pp. 680—685, November 3-6, 2014, Venice, Italy.

Thank you