Learning Customer Preferences and Voltage Regulation

The Interweaving of Humans and Physical Systems: A Perspective from Power Systems

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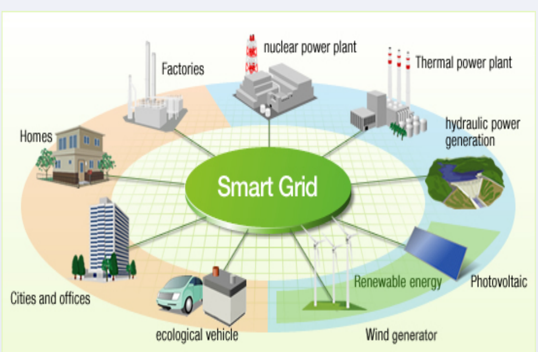
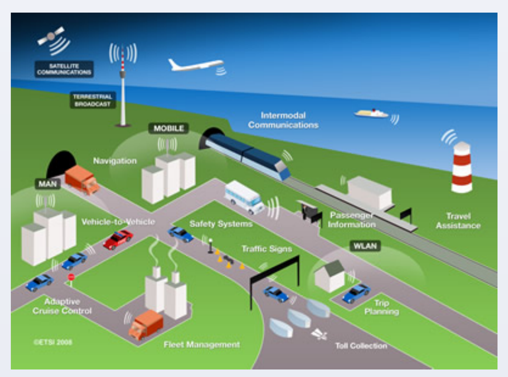
Introduction

Learning is becoming an integral part of many cyberphysical systems:





- Lots of uncertainty in the system, especially with respect to human users
- Physical constraints must be respected

Challenges:

- Systems needs to be learned quickly and efficiently
- Humans in the loop: time-varying and uncertain
- Labeling data is often expensive
- Small data: limited number of trials, often under high-dimensional settings
- Data arrives in sequential fashion

Approaches:

- Strategically make use of limited data
- Carefully designed algorithms: learn what is possible
- Use ”direct” algorithm when appropriate: bypass fitting an explicit model then optimizing
- Use online algorithms which can offer surprising performances
- Evaluate on real system and real data when possible
- Compare against offline optimal solutions

Students and Postdocs:

- Pan Li, Chase Dowling, Hao Wang

Learning Customers' Costs

- Demand response is an important tool used to the utilities to balance load and generation
- Utilities often do not have direct load control and do not know the cost function of the users

Objective: *Learn the correct price signals to send under limited number of signals*

Operator's Problem

- N users, with consumption x_i^t
- Operator has a target consumption Y_t
- Want to minimize

$$\alpha Y_t - \frac{1}{2}\left(\sum_{i==1}^{N} x_i^t - Y_t\right)^2$$

where the first term is the (negative) profit from demand response and the second term is the mismatch between the user response and the target

User's Response

- User has cost:

$$c_i(x_i^t) = \frac{1}{2}\beta_i (x_i^t)^2 + \alpha_i x_i^t$$

- Receives a payment of λ_t, so user i solves

$$x_i^t = \arg\min_x c_i(x) - \lambda_t x$$

- Noisy response:

$$\hat{x}_i^t = x_i^t + w_i^t$$

Online Learning

- The operators tries to solve

$$\min_{R,x} \sum_{t=1}^{T}\sum_{i=1}^{N}\frac{1}{N}\mathbb{E}\left(\frac{1}{2}\beta_i(x_i^t+\epsilon_i^t)^2 + \alpha_i(x_i^t+\epsilon_i^t)\right) + \sum_{t=1}^{T}\frac{1}{2N}\mathbb{E}\left[\left(R_t + \sum_{i=1}^{N}\epsilon_i^t - Y_t\right)^2\right]$$

$$\text{s.t. } R_t = \sum_{i=1}^{N} x_i^t \qquad (\lambda_t)$$

- The dual variable λ_t is the right price
- Operator updates its estimate of the users' parameters
- Only the aggregate is needed

Voltage Control

- Voltage control plays an important role in the operation of power systems
- High penetration of distributed energy resources and users behaviors introduce fast varying uncertainties

Objective: *Ensure reliable operation under these uncertainties using chance constraints*

Power Flow Model

- Given a distribution network, consider the Linear DistFlow model:

$$\mathbf{V} = \mathbf{RP} + \mathbf{XQ}$$

where V is the voltage, P is the active power, Q is the reactive power, R and X are constant matrices

- The active power P is uncertain: randomness in renewables and user behaviors

$$\mathbf{V} = \mathbf{RP} + \mathbf{XQ} + \boldsymbol{\epsilon}$$

Chance Constraints

- Control Q to ensure that voltages are safe

$$\min_{\mathbf{Q}} f(\mathbf{Q})$$

$$\Pr_{\boldsymbol{\epsilon}}\left(\underline{\mathbf{V}} \leq \mathbf{RP} + \mathbf{XQ} + \boldsymbol{\epsilon} \leq \overline{V}\right) \geq \beta$$

- The components of ϵ are highly correlated and the chance constraint is intractable even for Gaussian

Sample-Based Descent Algorithm

- Use a log-barrier function to convert to an unconstrained problem:

$$g_\lambda(\mathbf{Q}) = f(Q) - \lambda \log\left(\beta - \Pr_{\boldsymbol{\epsilon}}\left(\underline{\mathbf{V}} \leq \mathbf{RP} + \mathbf{XQ} + \boldsymbol{\epsilon} \leq \overline{V}\right)\right)$$

- Find a descent direction:

$$\mathbf{p} = \frac{g(\mathbf{Q} + \Delta \cdot \mathbf{e}) - g(\mathbf{Q})}{\Delta}\mathbf{e}$$

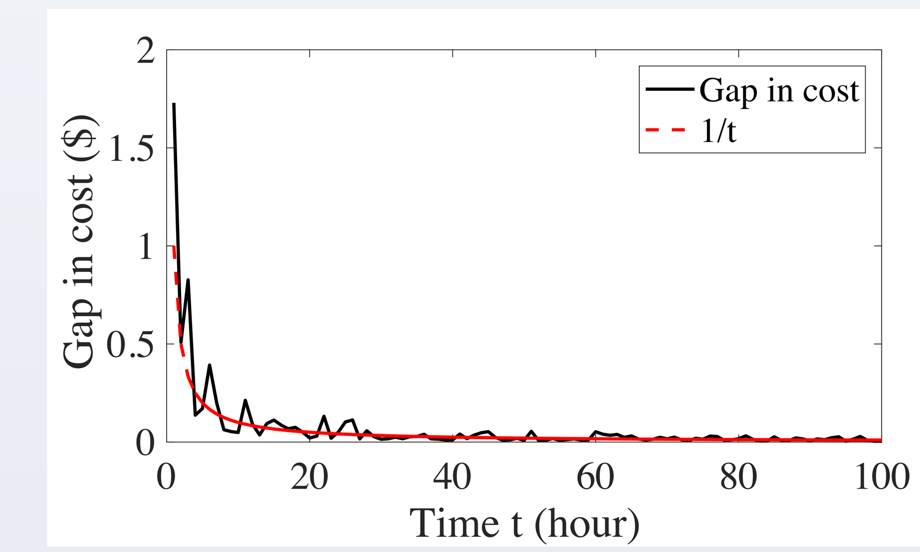
where e is a random direction and $\Delta \geq 0$

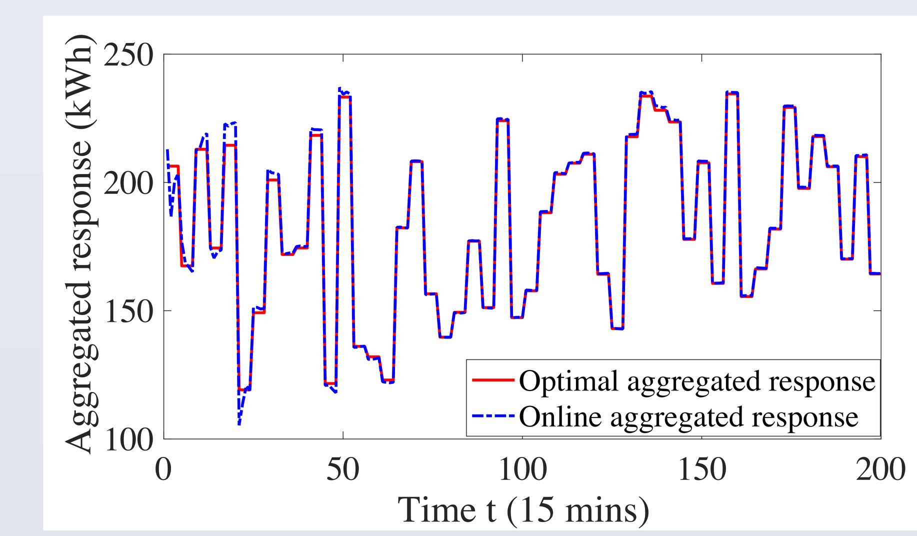
- With prob. 1, **-p** a descent direction
- The optimization problem can be shown to be convex for log-concave distributions
- The problem can be solved to optimal by just using historical data (without explicitly modeling the distribution)

Results

Online Learning:

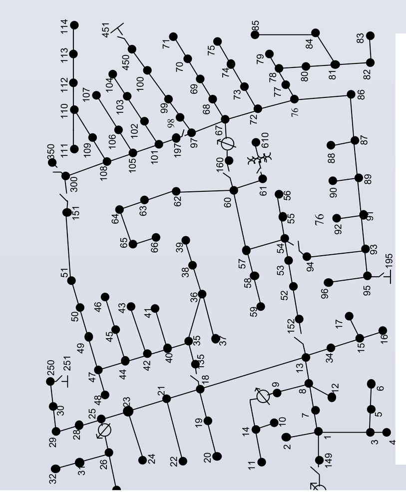
Optimal regret as the offline optimal algorithm

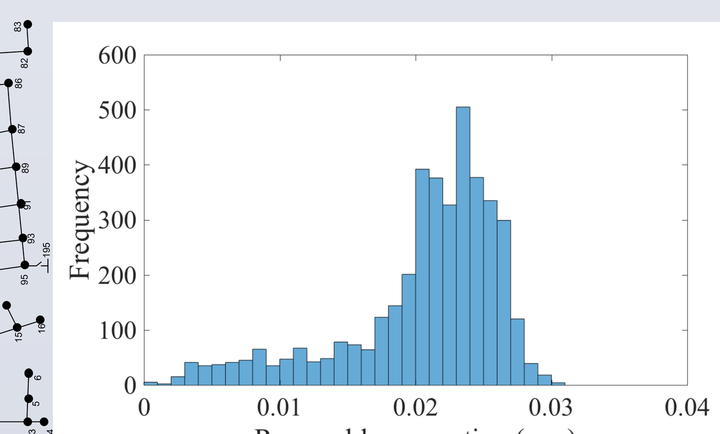




Voltage Control:

Much more efficient than integer programming





	BB	Algo. 1
Running time (seconds)	710	38
Empirical risk level	9.00%	8.97%
$\|\|Q\|\|_2$ (p.u.)	0.0083	0.0086
Most sensitive bus	104	104
Number of buses with non-trivial reactive power support	41	41

Publications

1. P. Li, H. Wang, B. Zhang, A Distributed Online Pricing Strategy for Demand Response Programs, IEEE Trans SmartGrid, 2017
2. P. Li, B. Jin, D. Wang, B. Zhang, Distribution System Voltage Control under Uncertainties using Tractable Chance Constraints, IEEE Trans Power Systems, 2018
3. C. Riquelme, R. Johari, B. Zhang, Online Active Linear Regression via Thresholding, AAAI, 2017