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Panel on "Domain-Specific Big Data Analytics Tools in Power Systems"

Online Learning and Optimization for Smart Power Grid

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Outline

- Background and motivation
- Online learning and optimization framework
- Applications

  A1) Real-time price setting for DR

  A2) Online optimal power flow

  A3) Online PMU data analysis
- Conclusion and future directions

Background and motivation

- Data deluge – power system is not an exception
  - Plethora of sensors (smart meters, smart phones, PMUs, …)
  - Networking technologies (high speed, low latency, IoT, ...)
  - Powerful analytics hardware/software
- Evolving landscape
  - More efficient and cleaner energy (smart grid, renewables, …)
  - Increasing demand (electric vehicle, data centers, ...)
  - Resiliency against uncertainty

Challenges and opportunities

- Big data challenges
  - Large volume → compression, sketching
  - High-rate → low-complexity, real-time processing
  - Dirty → cleansing, correction, security
  - Cyber-physical → closing the loop
- Opportunities
  - Enhanced monitorability
  - Power of statistical analysis/learning
  - From model-based to data-driven (Let the data speak!)

Online learning & optimization

- Online versus batch processing
  - Low latency, real-time
  - Streaming data
  - Low-complexity update
  - Track dynamic variations

- Universality, robustness
  - No need of detailed models (rather, law of large numbers)
  - Strong guarantees even under strategic (game) play

Online convex optimization framework

- OCO framework: game between a player and an adversary
  - At each time slot $t = 1,2,\ldots,T$
  - Player chooses $\mathbf{p}^t$
  - Adversary chooses $c^t(\cdot)$
  - Player suffers loss $c^t(\mathbf{p}^t)$ and receives feedback F^t
- OCO goal: produce $\{\mathbf{p}^t\}$ such that regret becomes sublinear

$$R_c(T) := \sum_{t=1}^{T} c^t(\mathbf{p}^t) - \min_{\mathbf{p}\in\mathcal{P}} \sum_{t=1}^{T} c^t(\mathbf{p}) \quad \text{with } R_c(T)/T \to 0 \text{ as } T \to \infty$$

Application: Real-time pricing for DR

- Demand response via pricing
  - Indirect load control via pricing/incentivization
  - Privacy preserving; naturally decentralized
- Real-time pricing based on consumer preference
  - Adjust energy pricing in real-time to shape load
  - Set prices/incentives differently for different customers
  - Load elasticity changes across consumer and time

Q: How to learn load elasticity robustly in real time with minimal modeling assumptions?

Problem formulation

- Model
  - p_k^t : price adjustment for customer *k* at time slot *t*
  - l^t : load level at slot *t without* price adjustment
  - θ_k^t : elasticity of consumer *k* at slot *t*
  - d_k^t : load adjustment of customer *k* due to price adjustment p_k^t

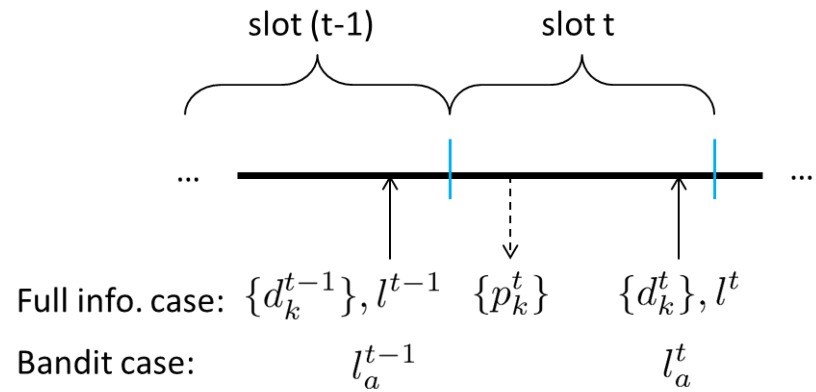
$$d_k^t = -\theta_k^t p_k^t \qquad \boldsymbol{\theta}^t := [\theta_1^t, \ldots, \theta_K^t]^\top$$

  - Aggregate adjusted load $l_a^t := l^t + \sum_{k=1}^K d_k^t = l^t - {\boldsymbol{\theta}^t}^\top \mathbf{p}^t$
- Objective: minimize load variance $\frac{1}{2}\sum_{t=1}^{T}\left(l^t - \boldsymbol{\theta}^\top \mathbf{p}^t - m^t\right)^2$
- Promote sparsity and fairness

$$\text{Minimize} \sum_{t=1}^{T} \overbrace{\Bigg[\underbrace{\frac{1}{2}\left(l^t - \boldsymbol{\theta}^\top \mathbf{p}^t - m^t\right)^2}_{:=\phi^t(\mathbf{p}^t)} + \underbrace{\lambda \|\mathbf{p}^t\|_1 + \frac{\mu}{2}\|\mathbf{p}^t\|_2^2}_{:=r(\mathbf{p}^t)}\Bigg]}^{c^t(\mathbf{p}^t)}$$

Algorithms

- Two types of feedback
  - Full feedback: $F^t = c^t(\cdot)$
  - Partial feedback: $F^t = c^t(\mathbf{p}^t)$ (better privacy)



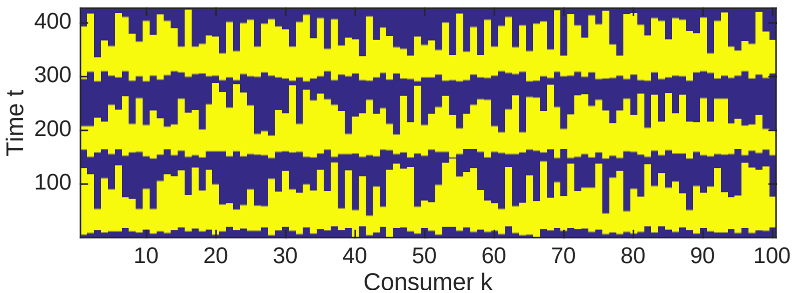
- Algorithm for full feedback case
  - Composite objective mirror descent (COMID) [Duchi et al.'10]

$$\mathbf{p}^{t+1} = \arg\min_{\mathbf{p}\in\mathcal{P}} \left[-\eta \underbrace{(l^t - {\theta^t}^\top \mathbf{p}^t - m^t){\theta^t}^\top}_{\nabla\phi^t(\mathbf{p}^t)} \mathbf{p} + \frac{1}{2}||\mathbf{p}-\mathbf{p}^t||_2^2 + \eta\left(\lambda||\mathbf{p}||_1 + \frac{\mu}{2}||\mathbf{p}||_2^2\right)\right]$$

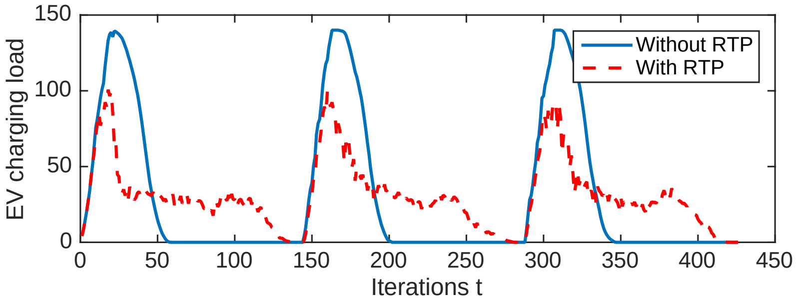
η: step size parameter

  - Provably achieves O(√T) regret bound

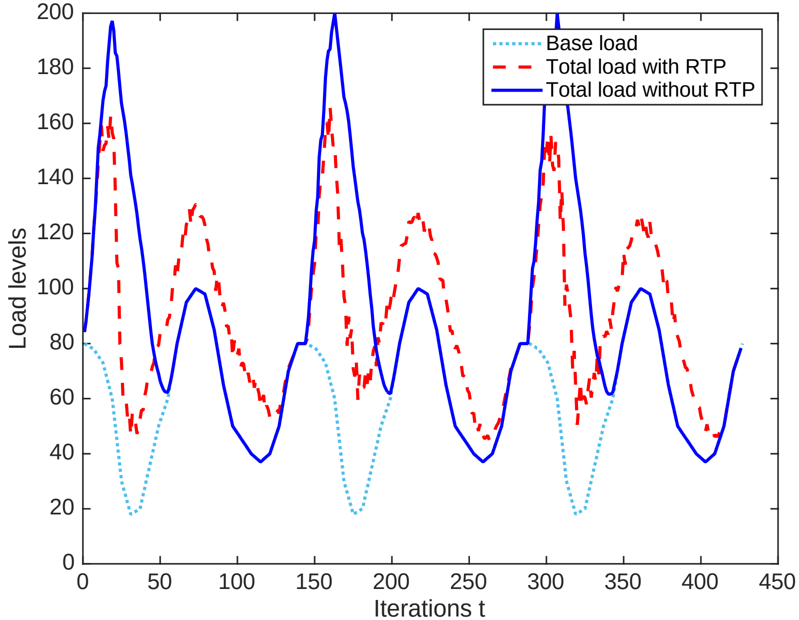
Numerical test for EV charging case



Requested EV charging start/end times



EV charging load



Total load (EV + base load)

S.-J. Kim and G. B. Giannakis, "An Online Convex Optimization Approach to Real-Time Energy Pricing for Demand Response," *IEEE Trans. on Smart Grid*, 2016 (to appear)

Online optimal power flow

- OPF is critical for efficient power system operation
  - Min. costs due to generation, losses, consumer disutility, etc.
  - Subject to: KCL, power balancing constraints
- Challenges
  - Nonconvexity (→ Convex relaxation)
  - Uncertainties (e.g. renewable generation)
- Existing approaches typically need elaborate models of uncertainty or computationally costly

Online OPF formulation

- A two-stage setup
  - In time slot *t* -1, decide generation levels $\{P_{g,n}^t\},\ n \in \mathcal{N}_g$ for slot *t*
  - In time slot *t*, use the spot market to balance supply & demand

- Cost must capture both generation and spot market transaction

$$c^t(\mathbf{p}_g^t) := \sum_{n \in \mathcal{N}_g} f_n(P_{g,n}^t) + g^t(\mathbf{p}_g^t)$$

$$g^t(\mathbf{p}_g^t) := \min_{\mathbf{X}^t \succeq 0, \{P_{s,n}^t\}, \{Q_{s,n}^t\}, \{Q_{g,n}^t\}} \sum_{n \in \mathcal{N}_s} g_n^t(P_{s,n}^t)$$

subject to

$$\underline{V}_n^2 \leq X_{nn}^t \leq \overline{V}_n^2, \quad n \in \mathcal{N}$$

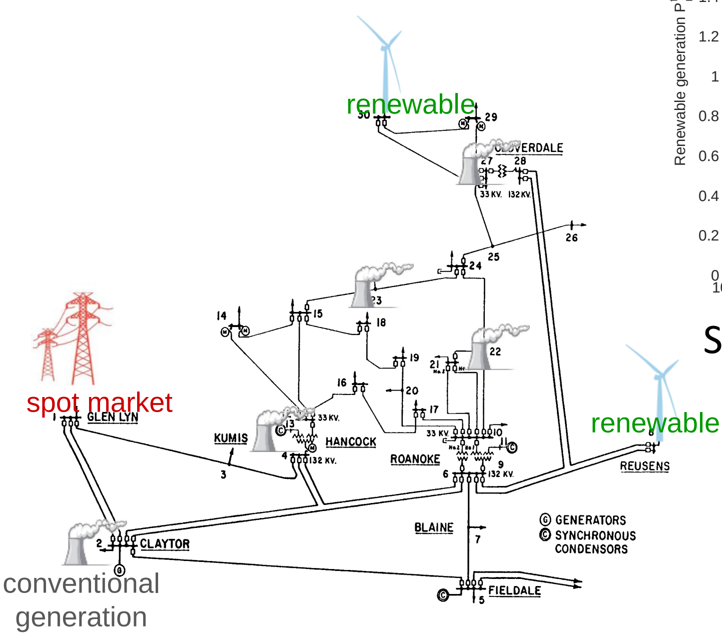
$$X_{nn}^t + X_{n'n'}^t - X_{nn'}^t - X_{n'n}^t \leq \overline{V}_{nn'}^2, \quad (n, n') \in \mathcal{E}$$

$$\mathrm{tr}\{\mathbf{X}^t \bar{\mathbf{Y}}_n\} - P_{g,n}^t + P_{l,n}^t - P_{r,n}^t - P_{s,n}^t = 0,\ \ n \in \mathcal{N}$$

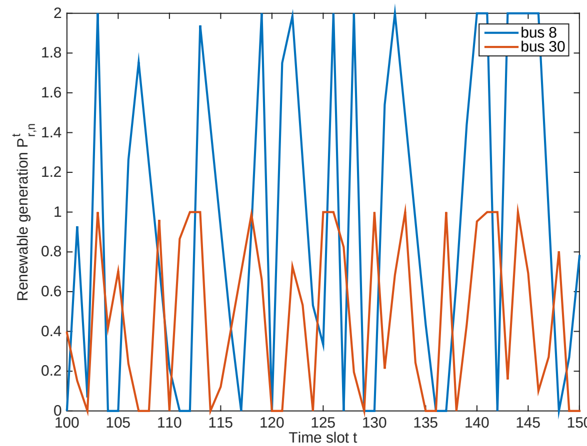
$$\mathrm{tr}\{\mathbf{X}^t \tilde{\mathbf{Y}}_n\} - Q_{g,n}^t + Q_{l,n}^t - Q_{r,n}^t - Q_{s,n}^t = 0, n \in \mathcal{N}$$

$$\underline{Q}_{g,n} \leq Q_{g,n}^t \leq \overline{Q}_{g,n}, \quad n \in \mathcal{N}_g$$

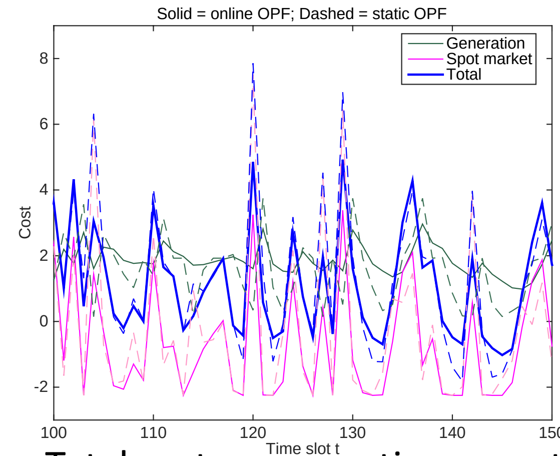
Simulated test results



IEEE test archive 30-bus case

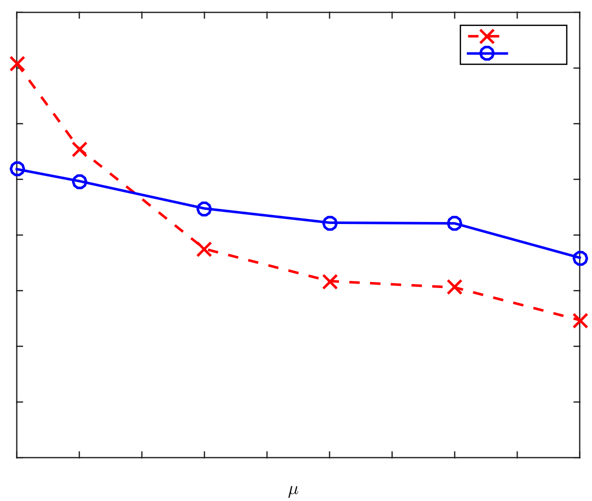


Simulated renewable generation



Total cost = generation + spot market cost

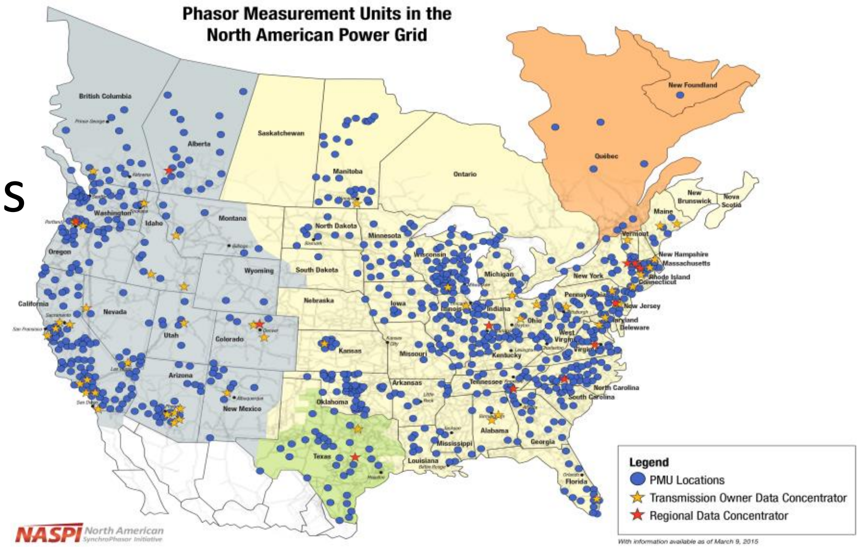
S.-J. Kim, G. B. Giannakis, and K. Y. Lee "Online optimal power flow with renewables," *in Proc. of the 48th Asilomar Conf. on Signals, Systems, and Computers*, Pacific Grove, CA, Nov. 2014.



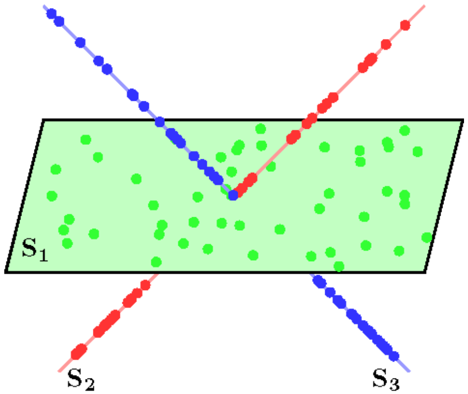
Average total cost of online & static OPF

Online PMU data analysis

- Phasor measurement unit (PMU)
  - High sampling rate: ~ 1 sample/20 ms
  - Precise synchronization across a wide area using GPS
  - Useful for monitoring dynamics of the power system
- Challenges with PMU data
  - Large volume of measurements
  - Fast and accurate inference
  - Incomplete measurements
  - Corrupt measurements



Method



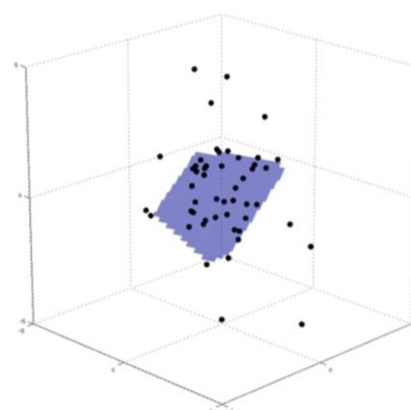
- Robust subspace clustering model
  - Data points are assumed to lie in a union of subspaces $\{\mathcal{S}_k\}$
  - Subspaces can capture different modes of grid operation

- Low rank representation [Liu et al.'13]
  - Postulate data have subspace structures contaminated by sparse outliers

$$\mathbf{Z} \approx \mathbf{X} + \mathbf{E}, \ \mathbf{X} \approx \mathbf{DC}$$

X : outlier-corrected component, **E** : sparse

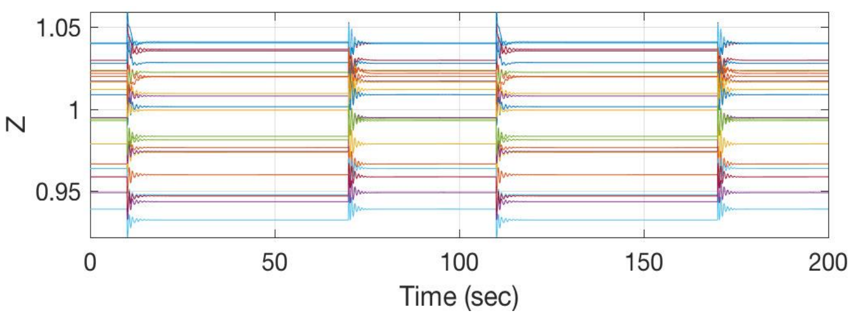
D : dictionary, **C** : low-rank

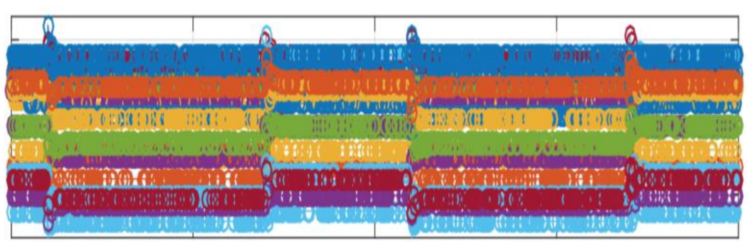


  - Our contribution: online algorithm

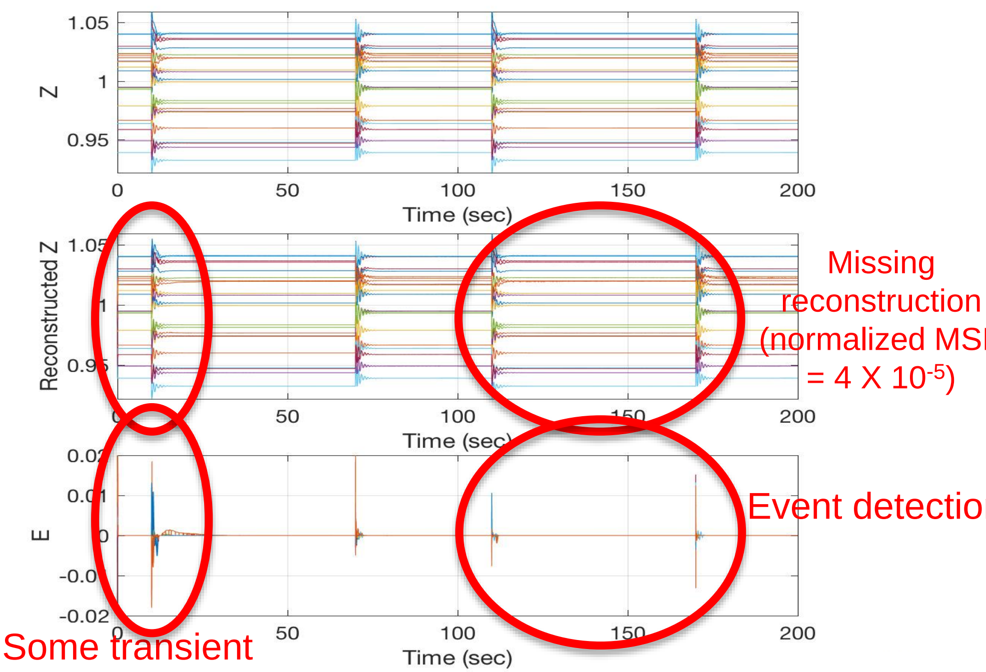
Results

- Simulated PMU data
  - 23-bus, 6-generator, 7-load test system simulated by PSS/E
  - Line trip at *t* = 10 and 110 sec; closed back at *t* = 70 and 170
  - Measurement Z are voltage magnitudes at all buses
  - 5% of measurement are missing





5% missing



Y. Lee and S.-J. Kim, ``Online robust subspace clustering for analyzing incomplete synchrophasor measurements," in *Proc. IEEE GlobalSIP*, Washington, DC, Dec. 2016.

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Conclusions and future work

- Online learning framework from machine learning
- Robust performance guarantees
- Versatile to various applications
  - Demand response
  - Power system monitoring and management
- Future directions
  - More sophisticated learning techniques
  - Closing the gap for cyber-physical interaction

Thank You