DOE/OE Transmission Reliability Program

Advanced Machine Learning for Synchrophasor Technology

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Aiming at (in 5-10 years)

Making

real-time monitoring situational awareness and control

under changing system conditions

using

PMU/data-driven and system-wide

Machine Learning (Applied Statistics) technology

a standard routine for power system utilities/practitioners

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Expected outcome (in 3 years)

Machine Learning approaches

- to identify parameters of
    - transmission network (static & dynamic)
    - generators (with controllers) & loads (passive and active)
- to detect network topology
- to estimate state (in parallel with all of the above)

normal/ambient

- develop taxonomy of events/anomalies
- localize events/anomalies

event

Demonstrate on reduced model of a selected utility (TBD)

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Anticipation beyond this project: 3+

1. For some of our methods and algorithms an additional fundamental R&D will be needed

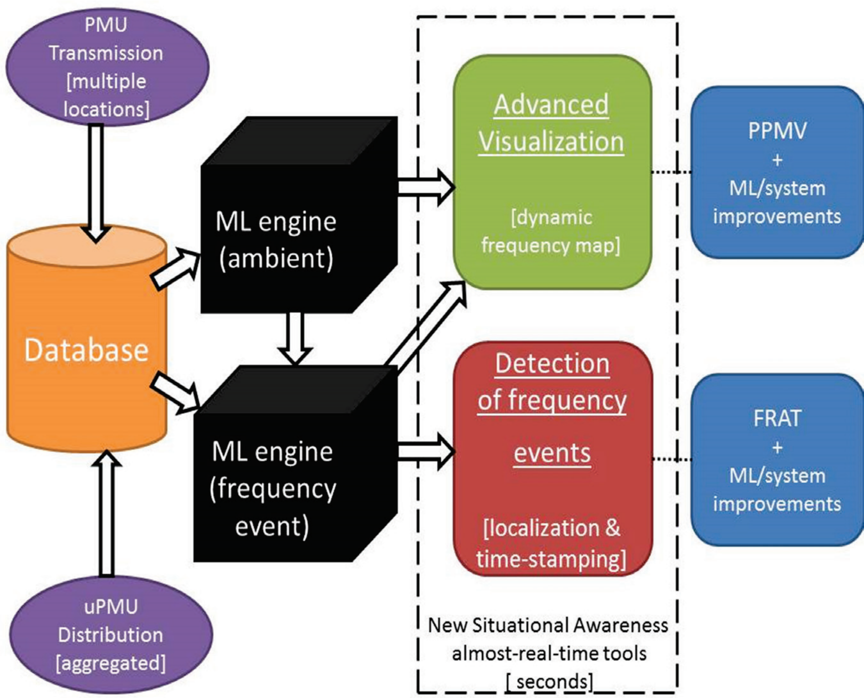
  - DOE/OE
  - +

2. Algorithms that are ready or nearly ready for technology transfer

  - DOE/APRA-E funding
  - CRADA with industry (third party vendors and start ups)
  - +

Project Features/Description

- Operating conditions are changing
- Operators do not have adequate tools for reliable situational awareness
- even though … PMUs data is available



- Need ***data-driven algorithms (engines)***:
  - state, topology & parameter estimations
  - event localization & timing
  - + visualization + situational awareness
    + embedding in & improving existing tools

Overall Project Objective

2016

Expected Outcomes --- Machine Learning and Analytics (MLA) toolbox

- Stochastic & dynamic modeling of the system
- New algorithms
  - State and Parameter estimation
  - Event localization
- Data-driven (synthetic → actual, PMU-measured)
- Validation and Integration into industry-grade platform(s)

2018

Looking Back: Major Accomplishments

[April 2016 -> June 2017]

- *Static Graphical Model Reconstruction*
- *Streaming PCA & Event Detection*
- *Topology Learning*
- *Latent State Estimation & Detection*
- *Grid/model reduction*

Main focus the first year:

new **algorithms**
for ambient and event regimes

Preliminary work towards industry-grade situational awareness platform

Major Modeling Principles behind our Algorithms

- **Scale separation** (spatial, temporal, voltage, phase)
  - e.g. state is changing fast, parameters slow
  - e.g. linearization around estimated AC solution

illustration

- **Model Reduction**
  - e.g. generalized swing equations with ``effective" damping, inertia, etc
  - e.g. principle components (in our PCA) are few

- **Parameter learning** - validated & calibrated in real time through measurements/data

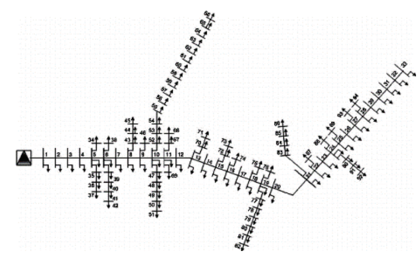
Model Reduction + Parameter learning

High fidelity models of parts

6th -order model of the plant

e.g. from PNNL/PPMV

Detailed model of the distribution



e.g. from LBNL including induction motors, transformers, other elements

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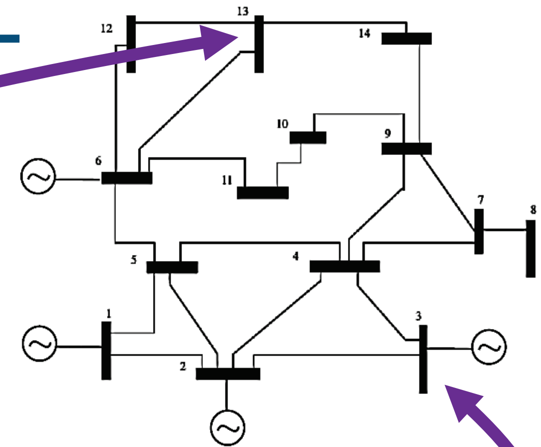
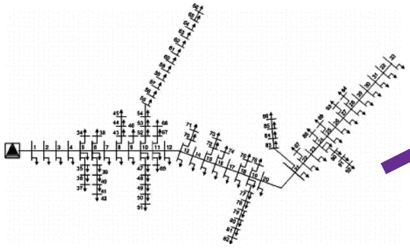
Model Reduction + Parameter learning



High fidelity models of parts

are substituted by reduced low-parametric models



where parameters are learned – from PMU system-wide measurements

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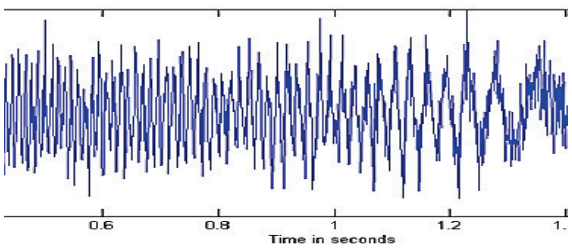
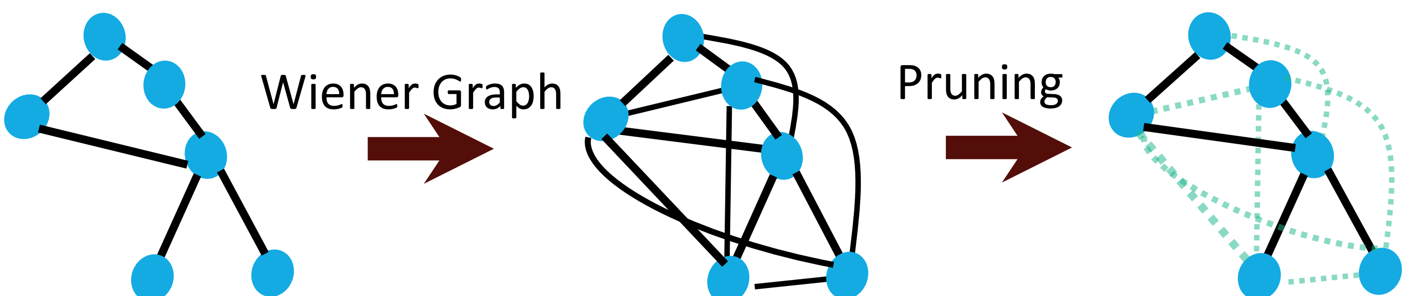
Highlights: Topology Detection

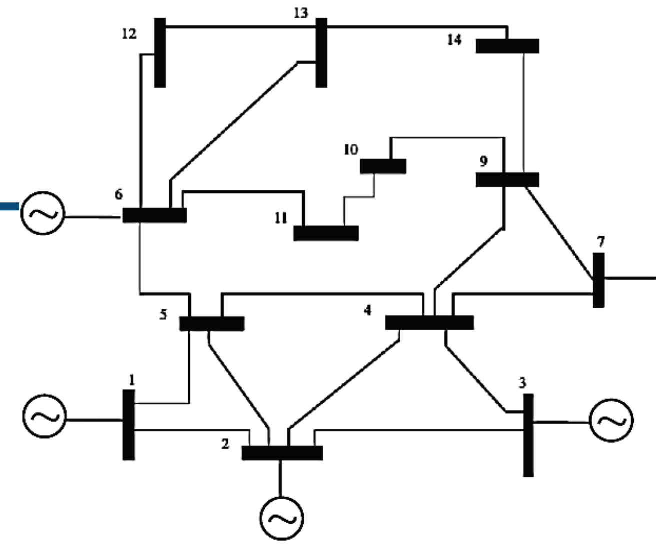
- Dynamic network eq. for normal transients
  - swing-eqs. or more complex dynamic. models of generators & loads
- Noise Model
  - Stochastic Wide-Sense Stationary



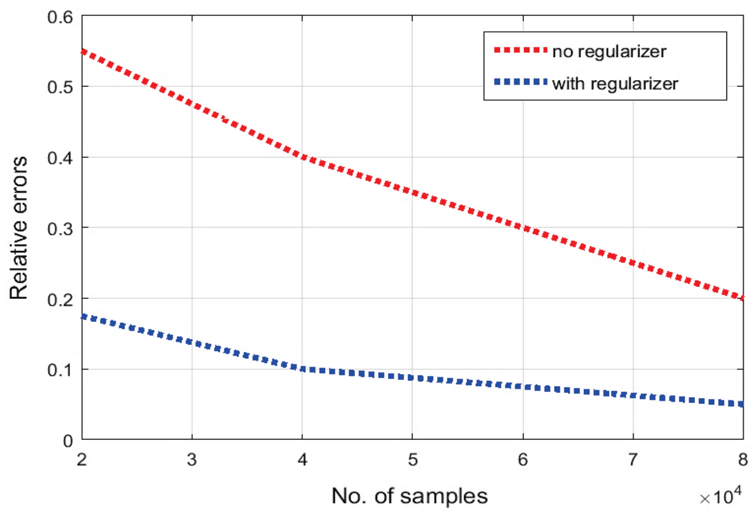
- Learn topology using (frequency response) filters
- New general method (do no need to know system parameters & noise details)
  - Precision matrix of phase (in Fourier domain) is constrained -> shows topology (implicitly)



Topology Detection

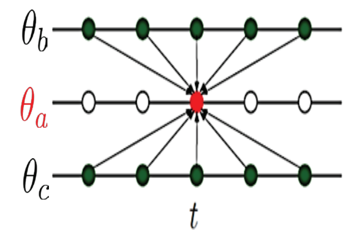


-- 14 bus system, sampling time= 0.01 sec



$$\min_{H_{ai}(z), i \neq a} \|\theta_a - \sum_{i \neq a} H_{ai}(z) X_i\|^2$$

$$+ \quad l_1 \quad \text{Regularizer}$$



<u>Path forward:</u>

- filter optimization
- sample complexity
- latent (sparse) detection
- robustness

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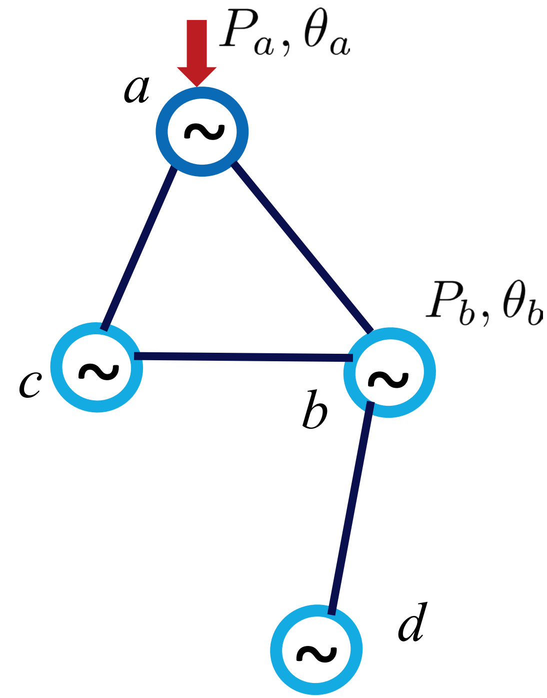
Highlight: Dynamic Parameter Estimation

- Discretize and Linearize Grid Dynamics

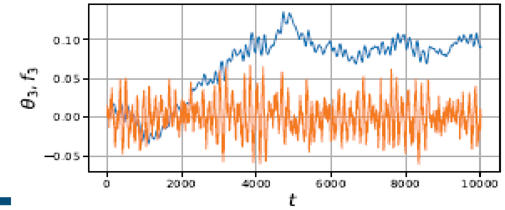
$$\theta_a^{t+1} - \theta_a^t = \Delta t f_a^t$$

$$f_a^{t+1} - f_a^t = \Delta t\Big(-\frac{D_a}{M_a} f_a^t + \sum_{(a,b)\ \text{is edge}} \frac{B_{ab}}{M_a}(\theta_b^t - \theta_a^t) + P_a^t\Big)$$

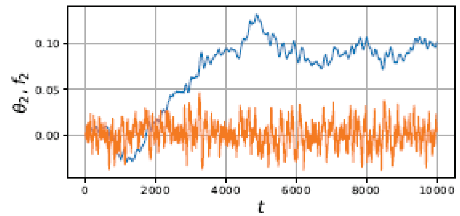


- l_2 Regression + Regularization:
  - Given: phase, frequency data
    -> reconstruct damping, inertia
  - Convex optimization with sample guarantees
  - topology + parameters are assumed known

Dynamic Parameter Estimation

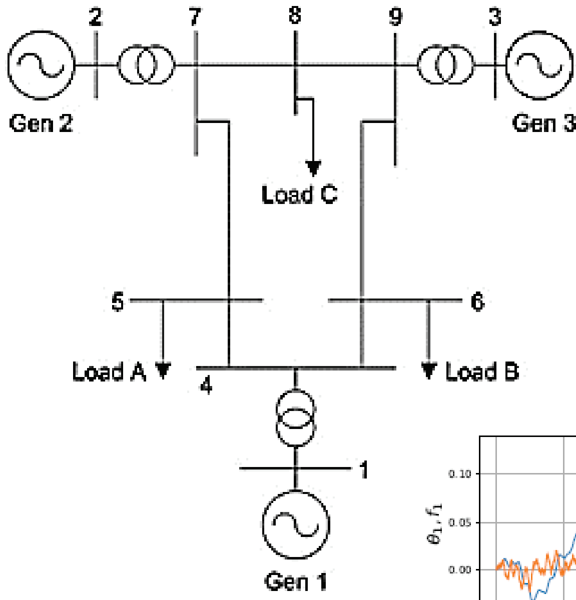


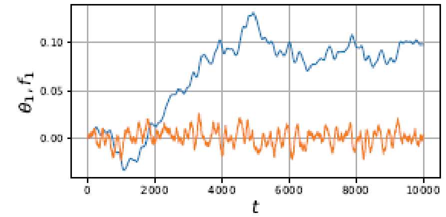
No. of samples	Error rate
1000	.09
10 000	.01
100 000	.003



9 bus, 3 generators

sampling time= 0.01 sec





Path forward:

- validation on industry-grade network models, e.g. extension of FRAT – situational awareness PNNL/BPA tool
- learning proper-order-reduced/effective dynamics
- joint state & parameter & topology estimations
- latent (partial observability) regime

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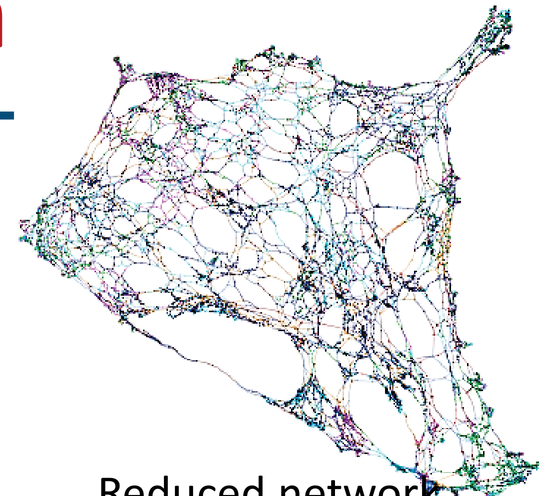
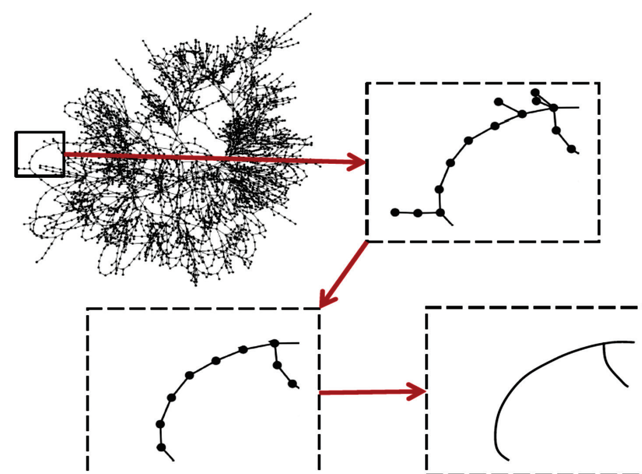
Highlights: Grid Reduction

- Physics & Topology aware reduction
  - Iterative degree-based
  - Reduce similar voltage nodes
  - Local reduction for topology consistency

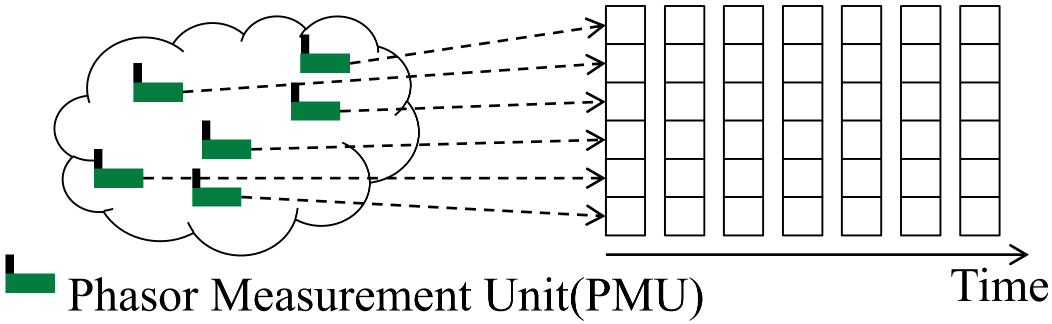


Reduced network

- Original network (actual mid-west utility)
  - ✓ 53,155 buses, 4332 generators.
  - ✓ 268 PMU devices
- Reduction Stages
  - ✓ 32,891 buses, 43,568 lines (degree 1)
  - ✓ 9,716 buses, 18700 lines (degree 2)
  - ✓ 6,732 buses, 11,079 (triangles)

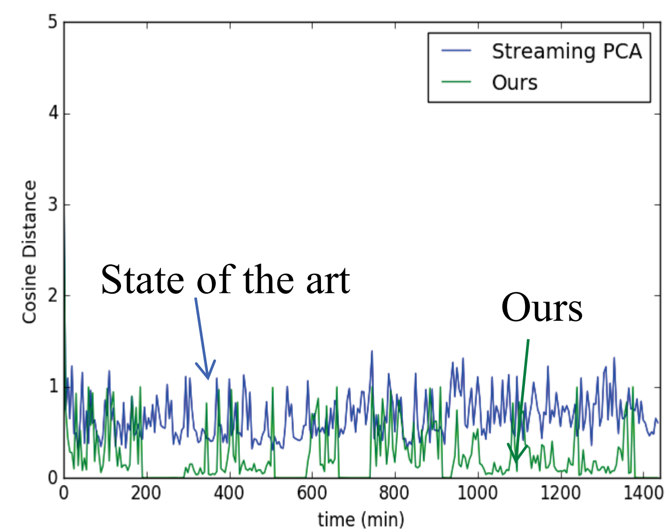


Highlights: Streaming Robust PCA

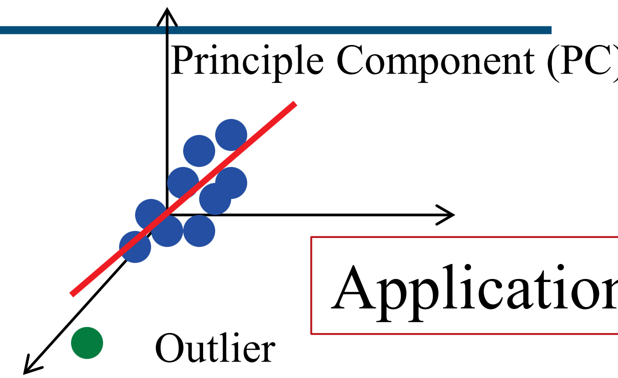


- 268 PMUs from a mid-west utility
- simultaneous phase covariance
- "model free"
- streaming (data storage is not needed)
- robust (universality, stability)

- New Robust Streaming Algorithm:
  - *Power Method* (non-stationary tracking)
  - + *Frequent Directions* (stable output)
- Reduced description:
  - 5-10 out of 268 eigenmodes are principle
  - others are dropped (assumed irrelevant = our data-verified model-reduction hypothesis)

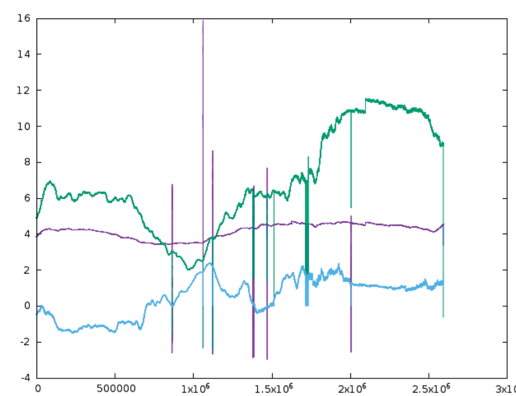


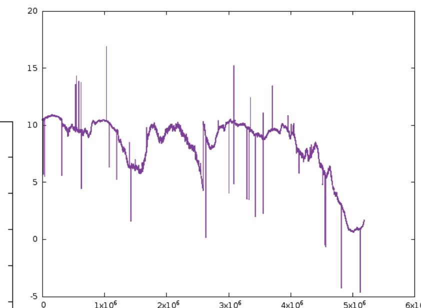
Highlights: Event Detection with PCA

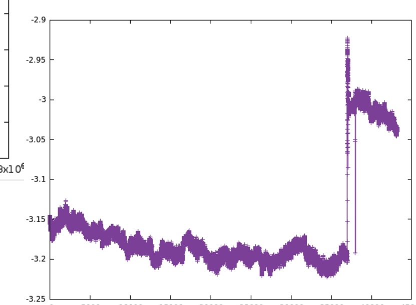


<u>Path forward:</u>

- Events = outliers
  - outlier instance = change of PC
- Supervised Learning of PC patterns [change detection]
  - Train on labeled events (taxonomy) from wind-farms, generators, transformers, etc
- Gradual enhancement towards physics-based modeling
- Integration into FRAT/PNNL +
- field tests with utility collaborator(s)
- spatio-temporal correlations & events







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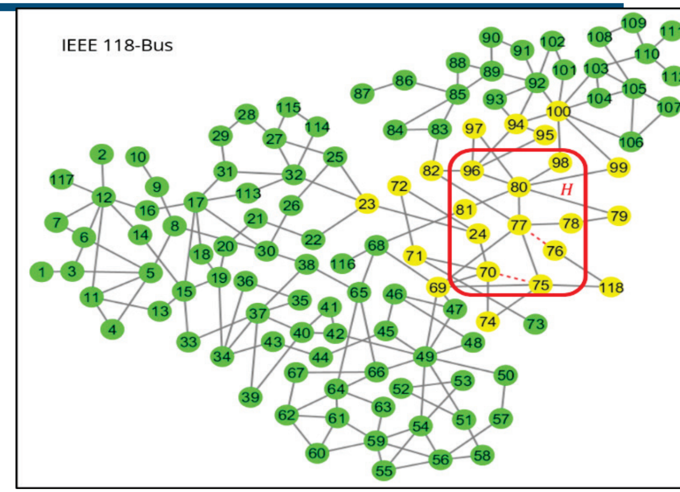
Highlights: Real or Communication event ?



Loss of visibility

- Detect: did PMU (communications) fail?
  Or was it a real/physical failure?

- Detectability of the affected area, H

- Estimate the invisible part of the state

Path Forward:

- Localize the affected area
- Robust PMU placement
- Comparisons, integration into FRAT/PNNL
- Field tests with utility collaborators

External Conditions on *H*	Internal Conditions on *H*	Constraints on the failures to be detected by the algorithm
Matching	Acyclic	None
Matching	Planar	Less than half of the edges in each cycle are failed
Partial Matching	Acyclic	Less than half of the edges connected to an internal node are failed
Partial Matching	Planar	Two of the above conditions

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(General) Model & Data Challenge

Dynamic Models and Data Generation:

- IEEE models + synthetic noise
  - dynamics of generators & consumers
  - small -> medium -> large

already in place

- IEEE models + synthetic noise
  - PSLF + (industry grade models)
  - More realistic synthetic noise, e.g. from actual PMU data and our algorithms

coming months

in 6-12 months

- Real Data/measurements (from our industry partners)

in 18-24 months

- Online field tests with an industry partner

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Other General Challenges

Machine Learning as an advisory tool
(for practical situational awareness)

- Online streaming — already in place
- Partial/latent observations — coming months
- Robust to noise, corruption, etc — in 6-12 months
- Controlled perturbations to improve observability = reinforcement learning — in 18-24 months

Looking Forward: Activities & Schedule

Short term:

- Regular bi-weekly meetings
- Multiple submissions to PSSC (extended abstracts, July 2)
- Presentation at NASPI on ambient learning (Sep 2017)
- Meeting with industrial partners
  (coordinated by D. Sobajic, Sep 2017)

List of Publications + more coming

[1] M. Vuffray, A. Lokhov, S. Misra, and M. Chertkov, "Interaction Screening: Efficient and Sample-Optimal Learning", NIPS 2016.
[2] A. Lokhov, M. Vuffray, S. Misra, and M. Chertkov, "Optimal structure and parameter", under consideration in Science.
[3] S. Misra, M. Vuffray, A. Lokhov, M. Chertkov "Towards Optimal Sparse Inverse Covariance Selection through Non-Convex Optimization," submitted to NIPS, 2017
[4] S. Yun, "Noisy Power Method with and without Spectral Gap", submitted
[5] S. Talukdar, D. Deka, M. Chertkov, M. Salapaka, "Learning Exact Topology of a Loopy Power Grid from Ambient Dynamics", ACM e-energy 2017.
[6] S. Soltan, M. Yannakakis, G. Zussman, "Power grid state estimation following a joint cyber and physical attack," IEEE Trans. Control of Network Systems (to appear), 2017.
[7] S. Soltan, A. Loh, G. Zussman, "On the Reproducibility of the Structural and Spatial Characteristics of Power Grids," submitted.
[8] H. Cetinay, S. Soltan, F. Kuipers, G. Zussman, P. Van Mieghem, "Comparing the Effects of Failures in Power Grids under the AC and DC Power Flow Models," under revision in IEEE Trans. Network Science and Engineering, 2017.
[9] S. Soltan, M. Yannakakis, G. Zussman, "Doubly Balanced Connected Graph Partitioning," Proc. ACM-SIAM SODA'17.
[10] D. Bienstock, C. Matke, S. Yang and G. Munoz, Robust linear control of storage in transmission systems, and extensions to robust network control, submitted.
[11] G. Munoz, D. Bienstock, LP approximations for mixed-integer polynomial optimization problems, INFORMS 2016.
[12] S. Soltan and G. Zussman, "Power grid state estimation after a cyber-physical attack under the AC power flow model," in Proc. IEEE PES-GM'17 (to appear), 2017.
[14] S. Soltan, A. Loh, and G. Zussman, "Quantifying the Effect of k-line Failures in Power Grids," Minor revision submitted IEEE Transactions on Control of Network Systems, 2017.
[15] M. Chertkov, D. Krishnamurthy, S. Misra, P. Van Hentenryck, and M. Vuffray, Graphical Models and Belief Propagation-hierarchy for Optimal Physics-Constrained Network Flows, to appear in a Springer book chapter.
[16] C. Grudzien, D. Deka, M. Chertkov, S. Backhaus, Structure and physics preserving reduction of power grid models, in preparation.

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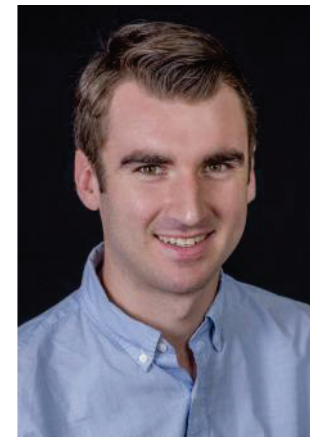
Thanks! Questions?

P. Etingov
(PNNL)

D. Deka
(LANL)

M. Vuffray
(LANL)



C. Roberts
(LBNL)

(in the audience)

What we don’t do directly …

but collaborate with other GMLC projects on

- ML for distribution wrt model reduction/aggregation
  - with GMLC 1.4.9

- Real Time Contingency Analysis & ``new protection” through analysis & optimization
  - GMLC Cat2 0076