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
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)

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

Demonstrate on reduced model of a selected utility (TBD)
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

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)
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

- **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
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.
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

Path forward:

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

\[
\min_{H_{ai}(z), i \neq a} \left\| \theta_a - \sum_{i \neq a} H_{ai}(z)X_i \right\|^2 + \ell_1 \text{ Regularizer}
\]
Highlight: Dynamic Parameter Estimation

- Discretize and Linearize Grid Dynamics

\[
\theta_{a}^{t+1} - \theta_{a}^{t} = \Delta t f_{a}^{t}
\]
\[
f_{a}^{t+1} - f_{a}^{t} = \Delta t \left( -\frac{D_{a}}{M_{a}} f_{a}^{t} + \sum_{(a,b)} \frac{B_{ab}}{M_{a}} (\theta_{b}^{t} - \theta_{a}^{t}) + P_{a}^{t} \right)
\]

- \(L_{2}\) Regression + Regularization:
  - Given: phase, frequency data
  - \(\rightarrow\) reconstruct damping, inertia
  - Convex optimization with sample guarantees
  - topology + parameters are assumed known
Dynamic Parameter Estimation

<table>
<thead>
<tr>
<th>No. of samples</th>
<th>Error rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>.09</td>
</tr>
<tr>
<td>10 000</td>
<td>.01</td>
</tr>
<tr>
<td>100 000</td>
<td>.003</td>
</tr>
</tbody>
</table>

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
Highlights: Grid Reduction

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

- 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

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)

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

State of the art

Ours
**Highlights: Event Detection with PCA**

**Path forward:**
- 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
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

<table>
<thead>
<tr>
<th>External Conditions on H</th>
<th>Internal Conditions on H</th>
<th>Constraints on the failures to be detected by the algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matching</td>
<td>Acyclic</td>
<td>None</td>
</tr>
<tr>
<td>Matching</td>
<td>Planar</td>
<td>Less than half of the edges in each cycle are failed</td>
</tr>
<tr>
<td>Partial Matching</td>
<td>Acyclic</td>
<td>Less than half of the edges connected to an internal node are failed</td>
</tr>
<tr>
<td>Partial Matching</td>
<td>Planar</td>
<td>Two of the above conditions</td>
</tr>
</tbody>
</table>
Dynamic Models and Data Generation:

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

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

- Real Data/measurements (from our industry partners)

- Online field tests with an industry partner
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

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