Real-time Synchrophasor Analytics: Data Quality Monitoring and Anomaly Detection

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PSERC

PSERC Webinar

March 7, 2017

Acknowledgements: Research Team

- Support from PSERC (Project S-71)

- S-71 Research Team:
  - Prof. Mani Venkatasubramanian (Washington State University)
  - Prof. P. R. Kumar (Texas A&M University)

- Students:
  - Dr. Yang Chen (now with PJM)
  - Ms. Meng Wu

Acknowledgements: Industry Advisors

- Aftab Alam, California ISO
- Frankie Zhang, ISO-New England
- Chaitanya A. Baone, GE Global Research
- Santosh Veda, GE Global Research
- Paul T. Myrda, EPRI
- Liang Min, LLNL
- Mahendra Patel, EPRI
- Giuseppe Stanciulescu, BC Hydro
- Vijay Sukhavasi, Alstom
- Gurudatha Pai, Alstom
- Jay Ramamurthy, Entergy
- Yingchen Zhang, NREL
- Prashant Kansal, AEP
- Harvey Scribner, SPP
- Jay Caspary, SPP
- Xiaoming Feng, ABB
- Floyd Galvan, Entergy
- Naim Logic, SRP
- Alan Engelmann, ComEd

Presentation Outline

- Introduction
- Part I: PMU Dimensionality Reduction & Early Event Detection
- Part II: Real-Time Detection of Low-Quality PMU Measurements
- Concluding Remarks

Motivation of This Work

PMU Challenges

- **<u>High dimensionality</u>:** Tennessee Valley Authority (TVA) 120 PMUs produces **36GB data per day**.
- **<u>State-of-the-art</u>:** primarily **offline, post-event analysis**.
- **<u>High Bad Data Ratio</u>:** Typical PMU bad data ratio in California ISO ranges from **10% to 17%** (in 2011).

Our Research

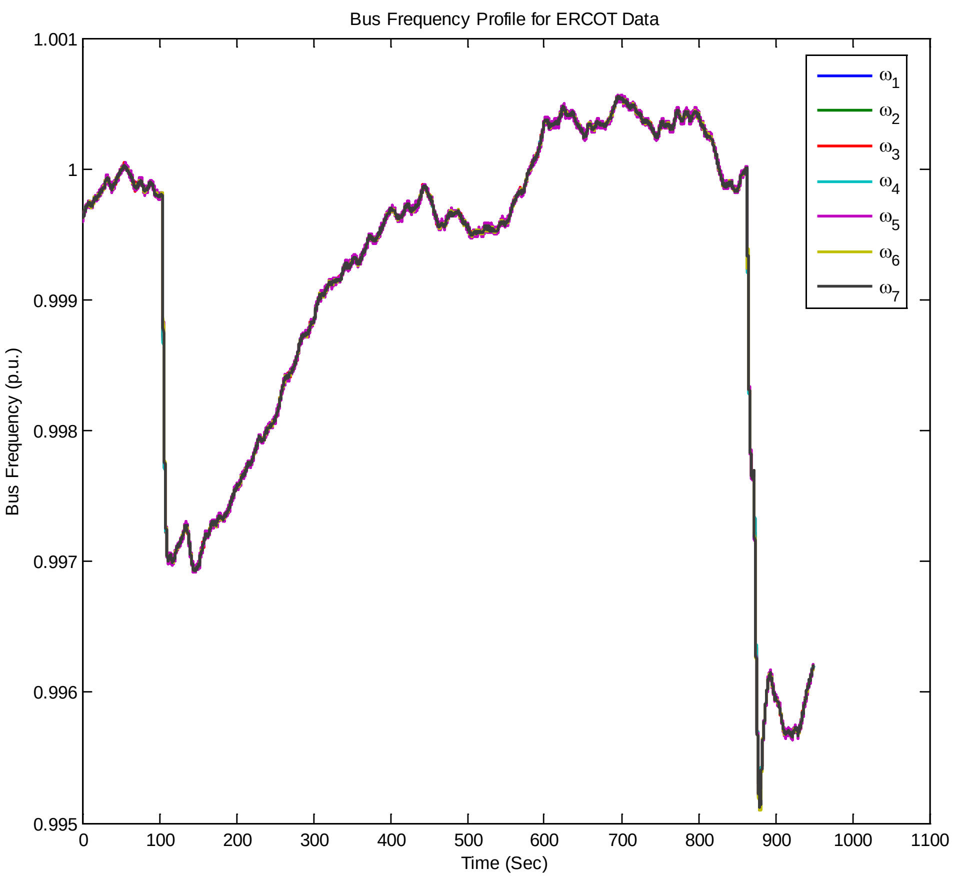
- ***Dimensionality reduction*** **of PMU measurements.**
- **Online *data-driven* PMU-based early event detection.**
- **Real-time *data-driven* PMU bad data detection.**

- [8] N. Dahal, R. King, and V. Madani, "Online dimension reduction of synchrophasor data," 2012.
- [9] M. Patel, S. Aivaliotis, E. Ellen et al., "Real-time application of synchrophasors for improving reliability," 2010.
- [5] California ISO, "Five year synchrophasor plan," California ISO, Tech. Rep., Nov 2011.

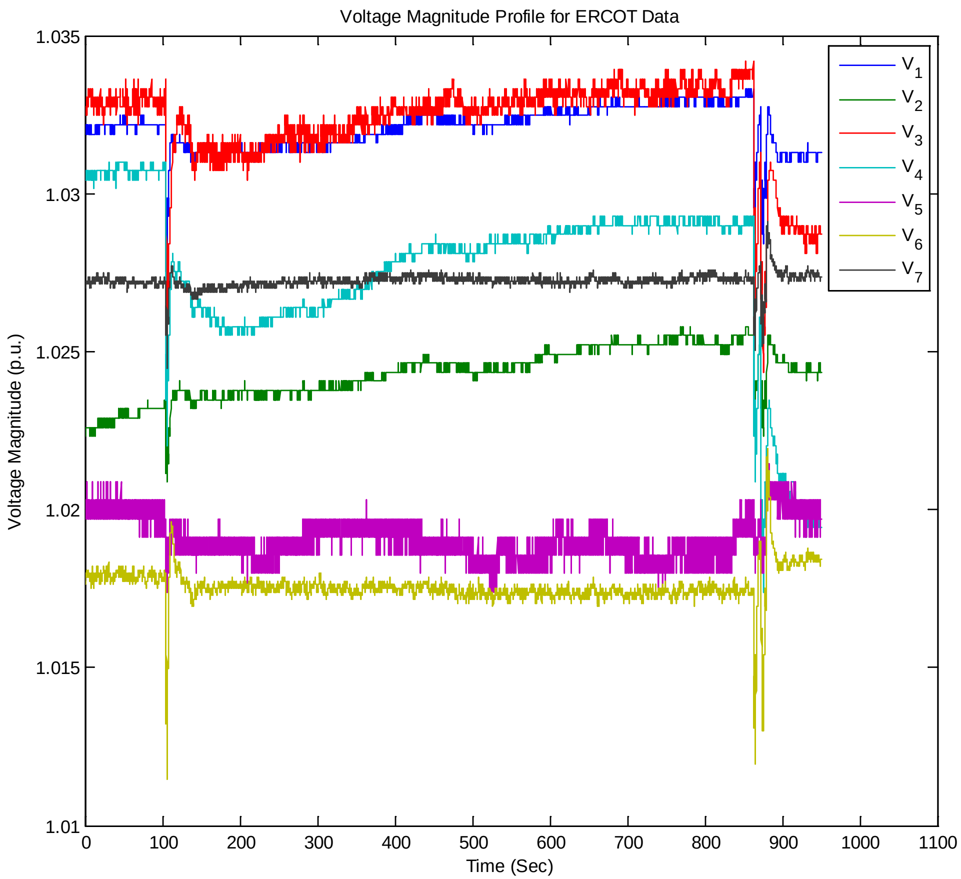
Presentation Outline

- **Introduction**
- **Part I: PMU Dimensionality Reduction & Early Event Detection**
- **Part II: Real-Time Detection of Low-Quality PMU Measurements**
- **Concluding Remarks**

Raw PMU Data from Texas



Bus Frequency Profile of ERCOT Data.



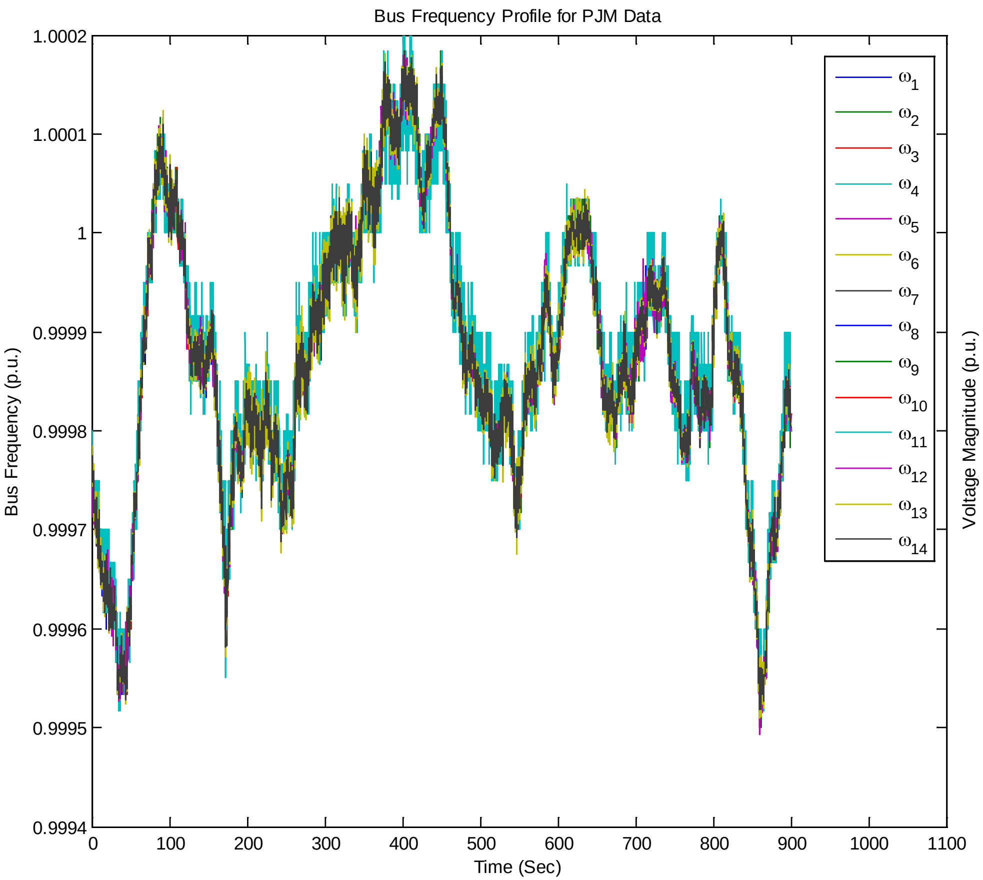
Voltage Magnitude Profile of ERCOT Data.

No system topology, no system model.

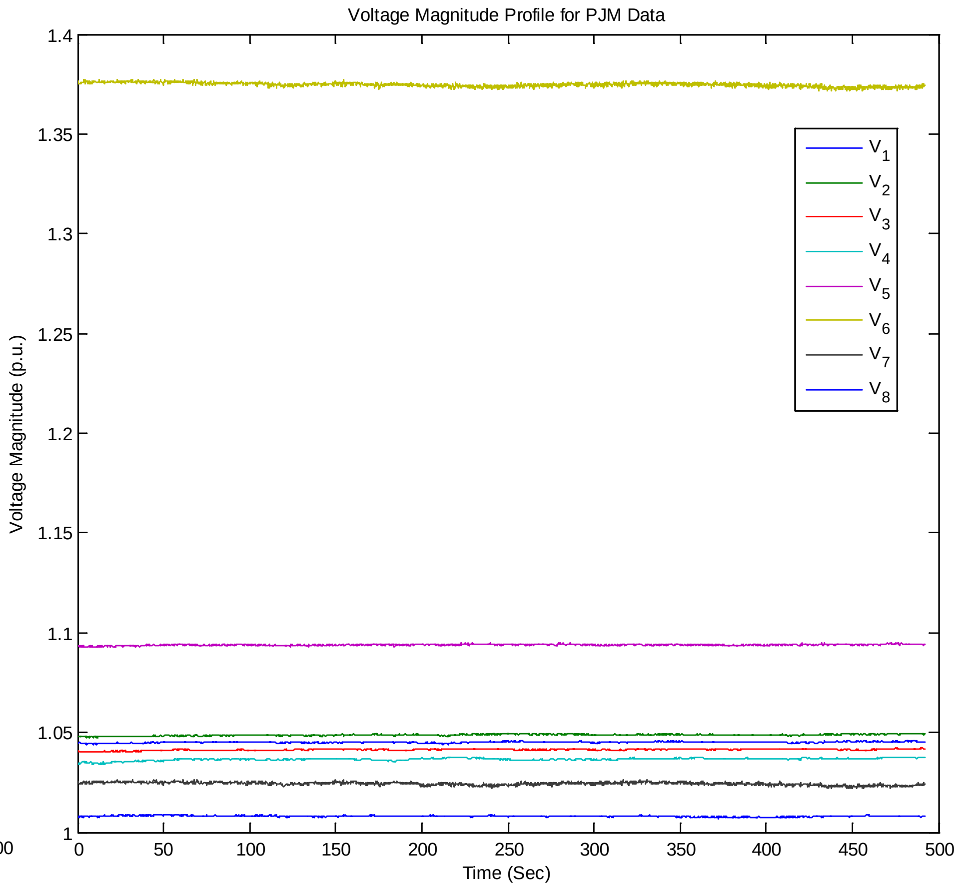
Total number of PMUs: 7.

- [6] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis," *IEEE Tran. Power Systems*, 2014.

Raw PMU Data from PJM



Bus Frequency Profile of PJM Data.



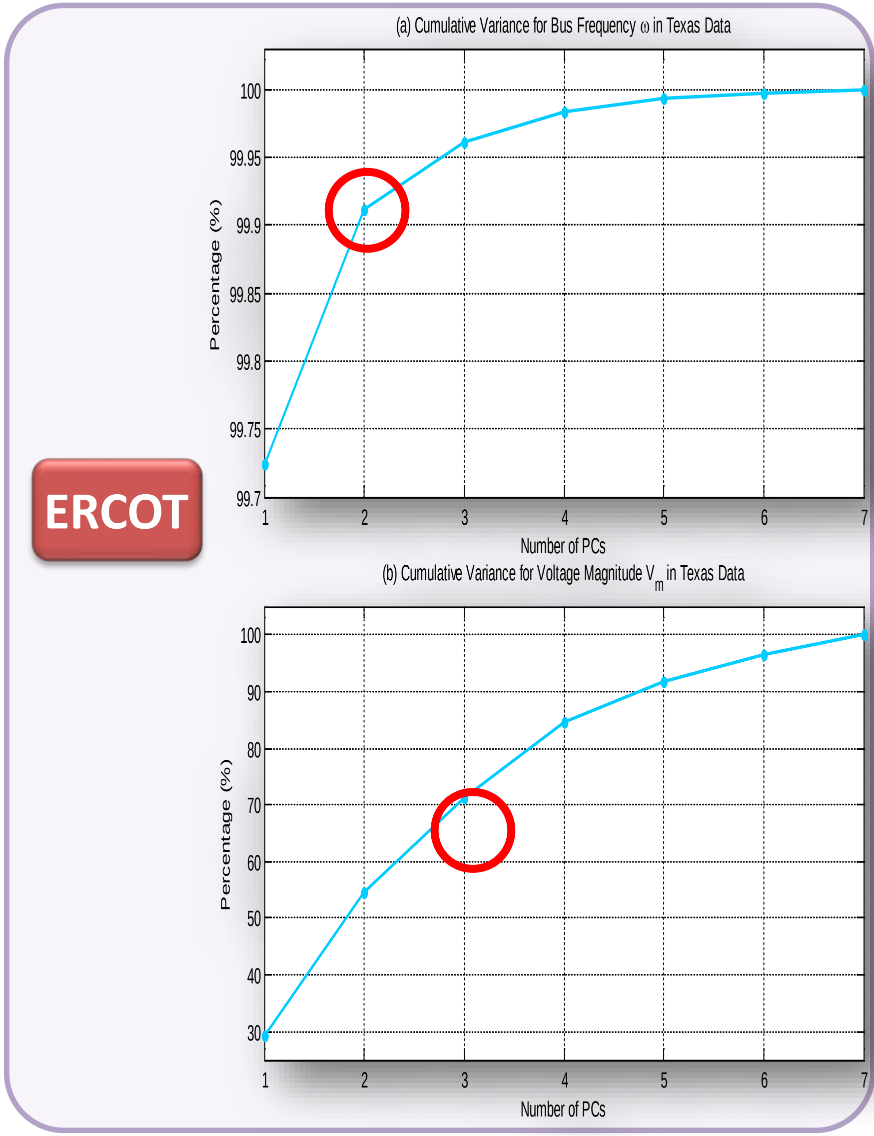
Voltage Magnitude Profile of PJM Data.

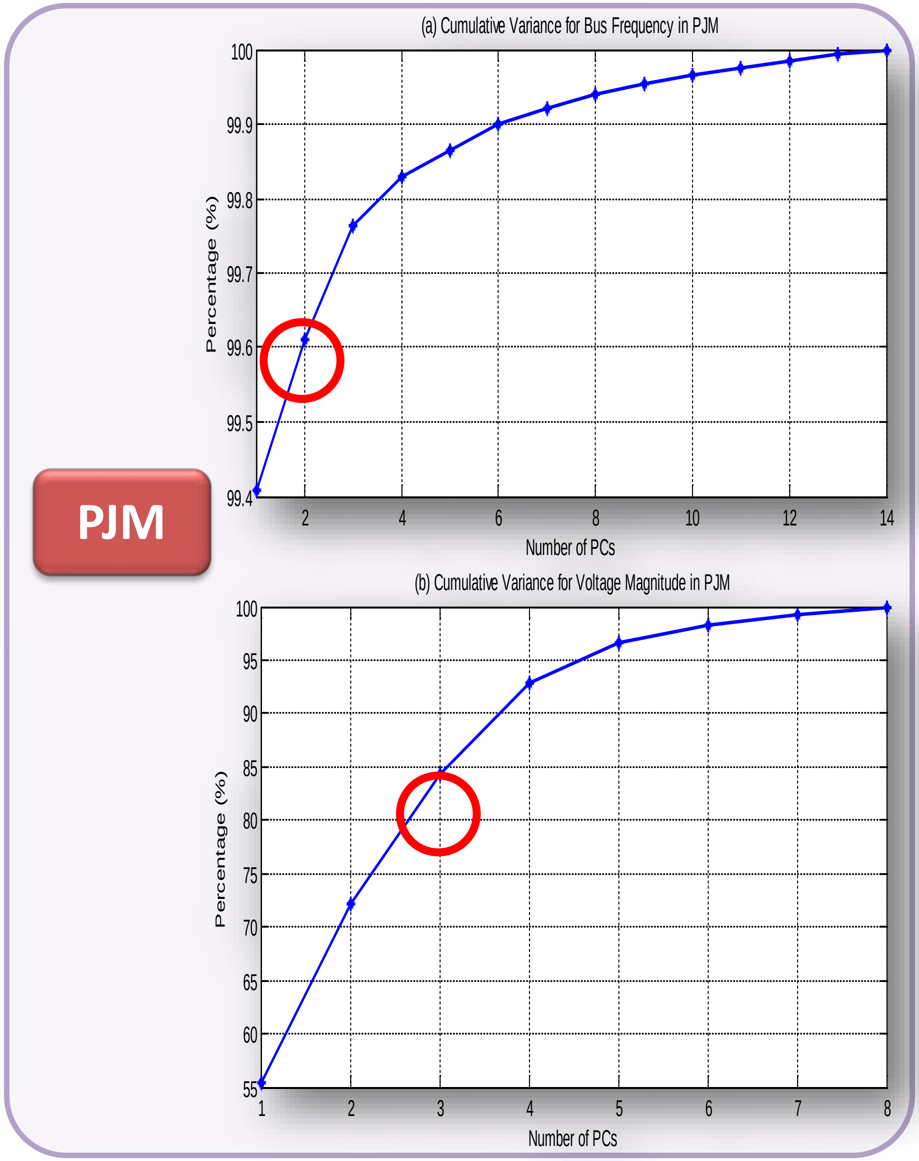
Total number of PMUs: 14 for frequency analysis

8 for voltage magnitude analysis.

- [6] L. Xie, Y. Chen, and P. R. Kumar, “Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis,” *IEEE Tran. Power Systems*, 2014.

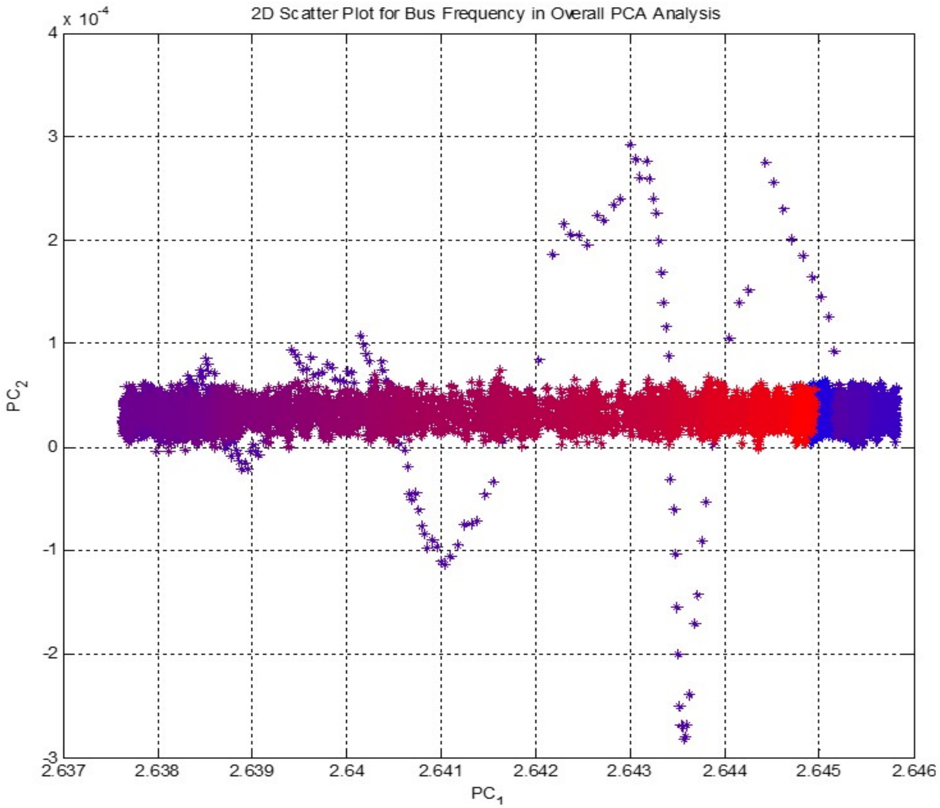
Dimensionality Reduction - PCA



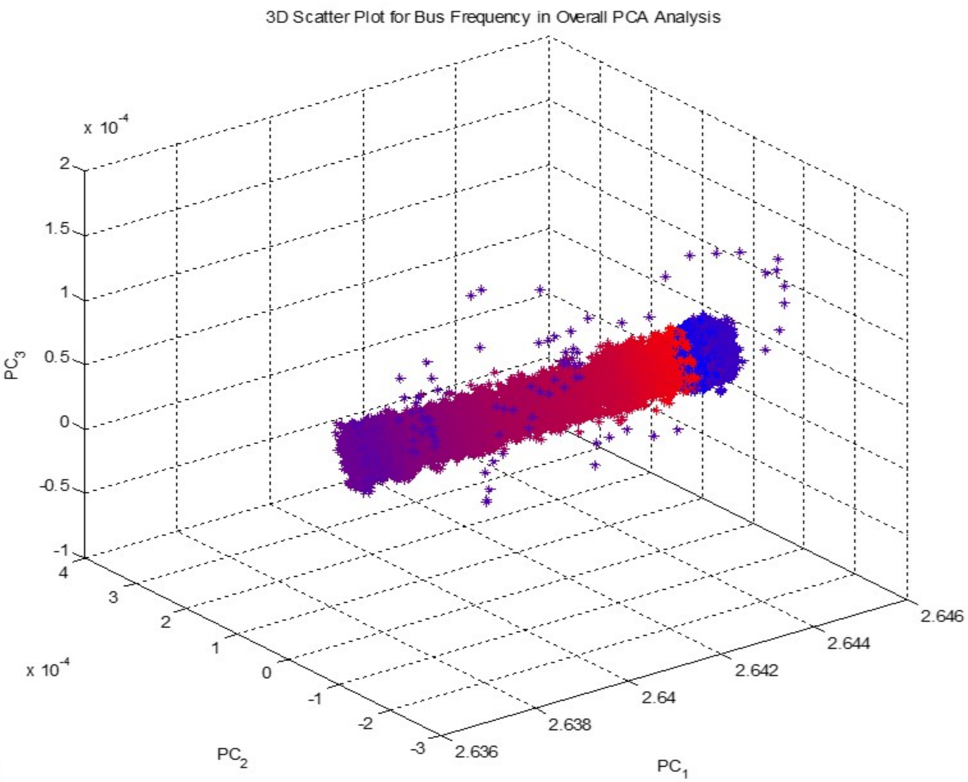


- PCA: Principal Component Analysis

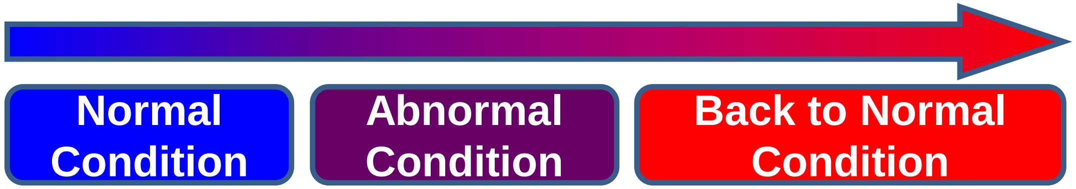
Scatter Plot of Bus Frequency



2D Scatter plot for bus frequency.

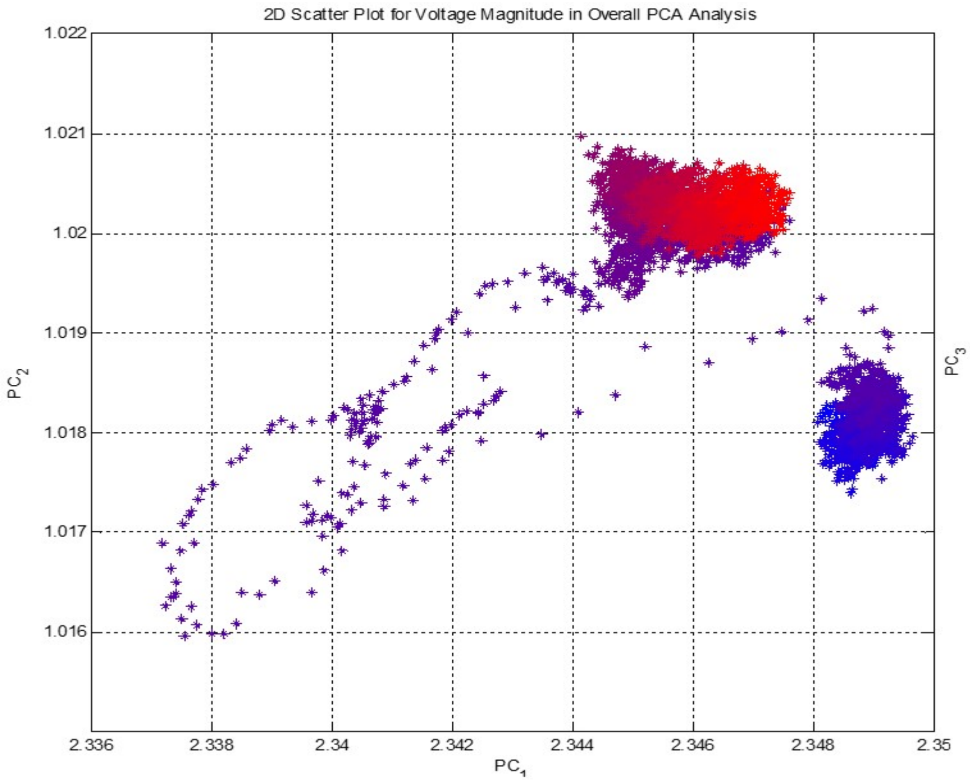


3D Scatter plot for bus frequency.

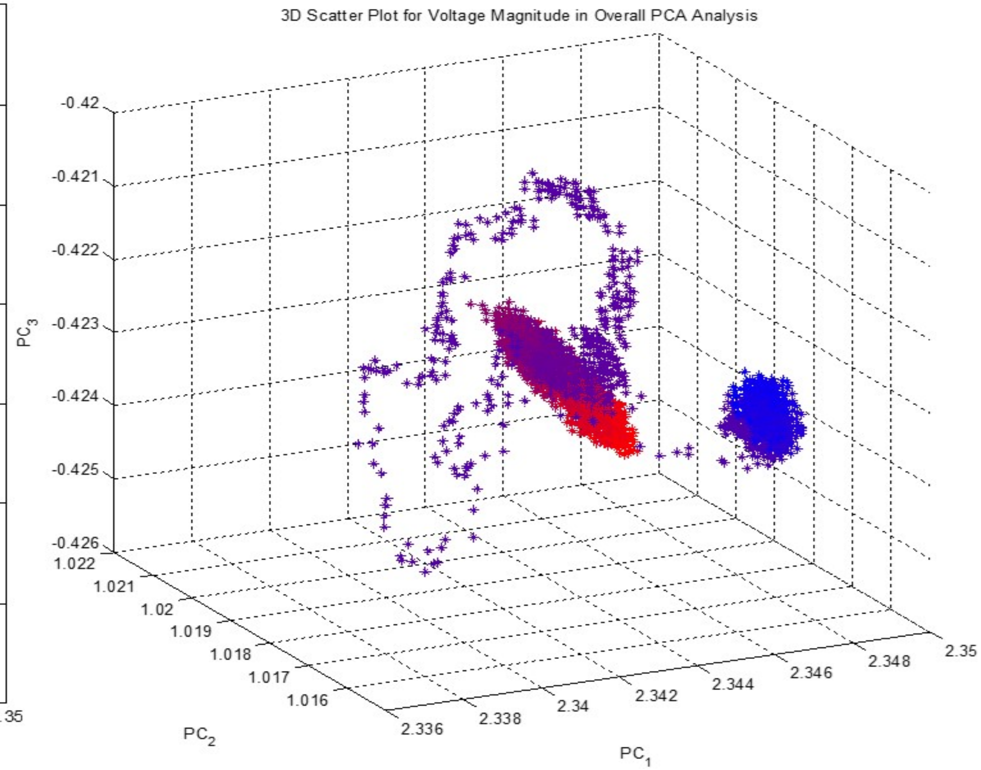


- [6] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis," *IEEE Tran. Power Systems*, 2014.

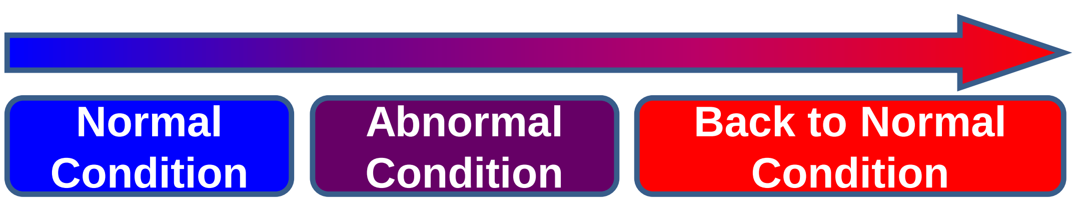
Scatter Plot of Voltage Magnitude



2D Scatter plot for voltage magnitude.



3D Scatter plot for voltage magnitude.



• [6] L. Xie, Y. Chen, and P. R. Kumar, “Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis,” *IEEE Tran. Power Systems*, 2014.

Observations

- High dimensional PMU *raw measurement* data lie in an *much lower* subspace (even with linear PCA)

- Scattered plots suggest that

  Change of subspace -> Occurrence of events !

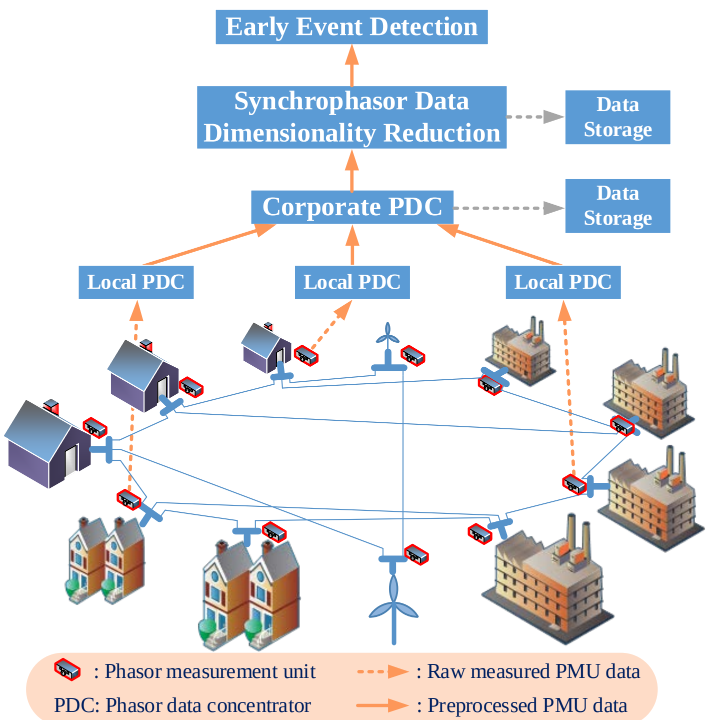
- But, what is the way to implement it?

- Is there any *theoretical* justification?

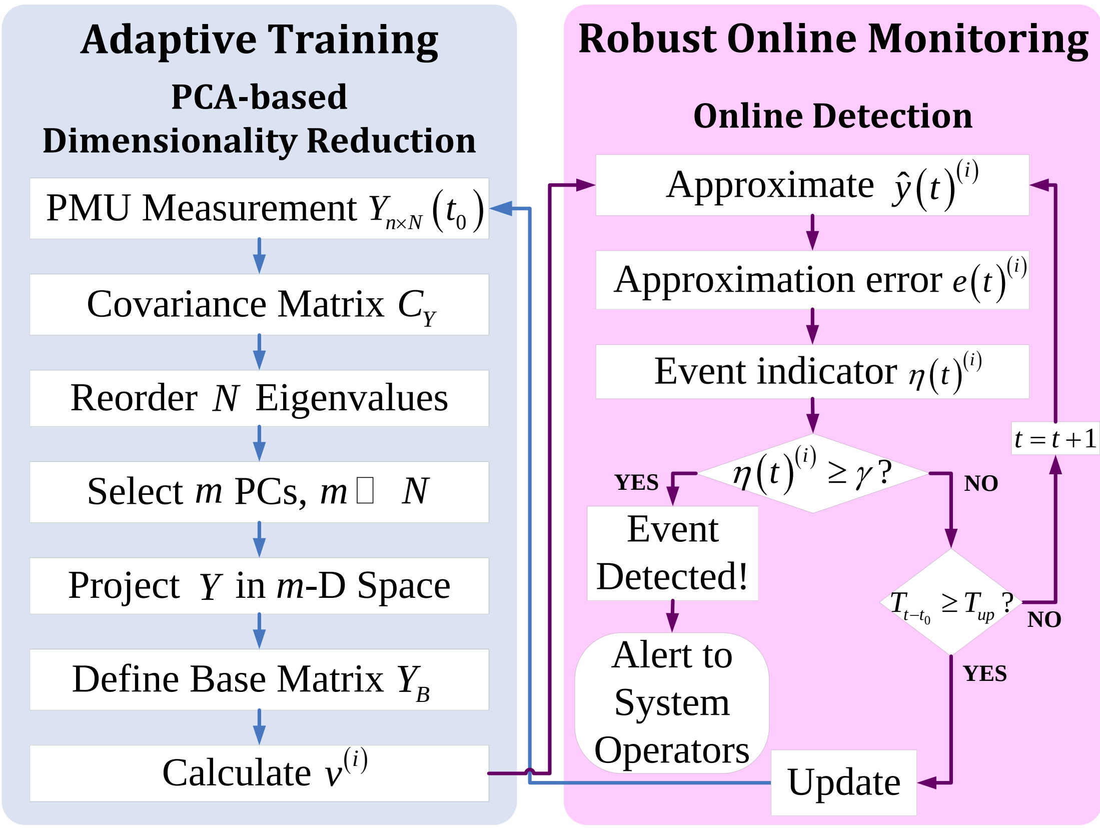
  Data-driven subspace change ⇔ Indication of physical events in wide-area power systems

- [6] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis," *IEEE Tran. Power Systems*, 2014.

Early Event Detection Algorithm



Early Event Detection Algorithm



Theoretically justified using linear dynamical system theory [6].

- [6] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis," *IEEE Tran. Power Systems*, 2014.

Theorem for Early Event Detection [6]

Theoretically justified

Using the proposed *event indicator*, a system event can be detected within 2-3 samples of PMUs, i.e., within 100 ms, whenever for some selected non-pilot PMU *i*, the event indicator satisfies

$$\left|\eta(t)^{(i)}\right| \geq \gamma$$

where γ is a system-dependent threshold and can be calculated using historical PMU data.

$$\eta(t)^{(i)} := \frac{e(t)^{(i)}}{e^{normal}} \qquad e(t)^{(i)} := \left|\frac{\tilde{y}(t)^{(i)}}{y(t)^{(i),meas}}\right| \times 100\%$$

- [6] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis," *IEEE Tran. Power Systems*, 2014.

Sketch of the Proof [6]

- Power system DAE model

$$\dot{x}(t) = f(x(t), u(t), h(t), q(t)),$$
$$0 = g(x(t), u(t), h(t), q(t)),$$

- Discretization

$$x[k+1] = A_d x[k] + B_d u[k] + \alpha[k],$$
$$y[k] = C_d x[k] + D_d u[k] + \varepsilon[k],$$

- Using back substitution, explicitly express output (measurement) *y[k]* in terms of initial condition *x[1]*, control input *u[k]*, noise *e[k]*

$$y[k] = C(e^{AT})^{k-1}x[1] + \sum_{l=1}^{k-1} C(e^{AT})^{l-1}A^{-1}(e^{AT} - I)Bu[k-l] + \varepsilon[k]$$
$$= y_x[k] + y_u[k] + y_\varepsilon[k],$$

- [6] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis," *IEEE Tran. Power Systems*, 2014.

Sketch of the Proof (conti.) [6]

- Normal conditions: training errors are small

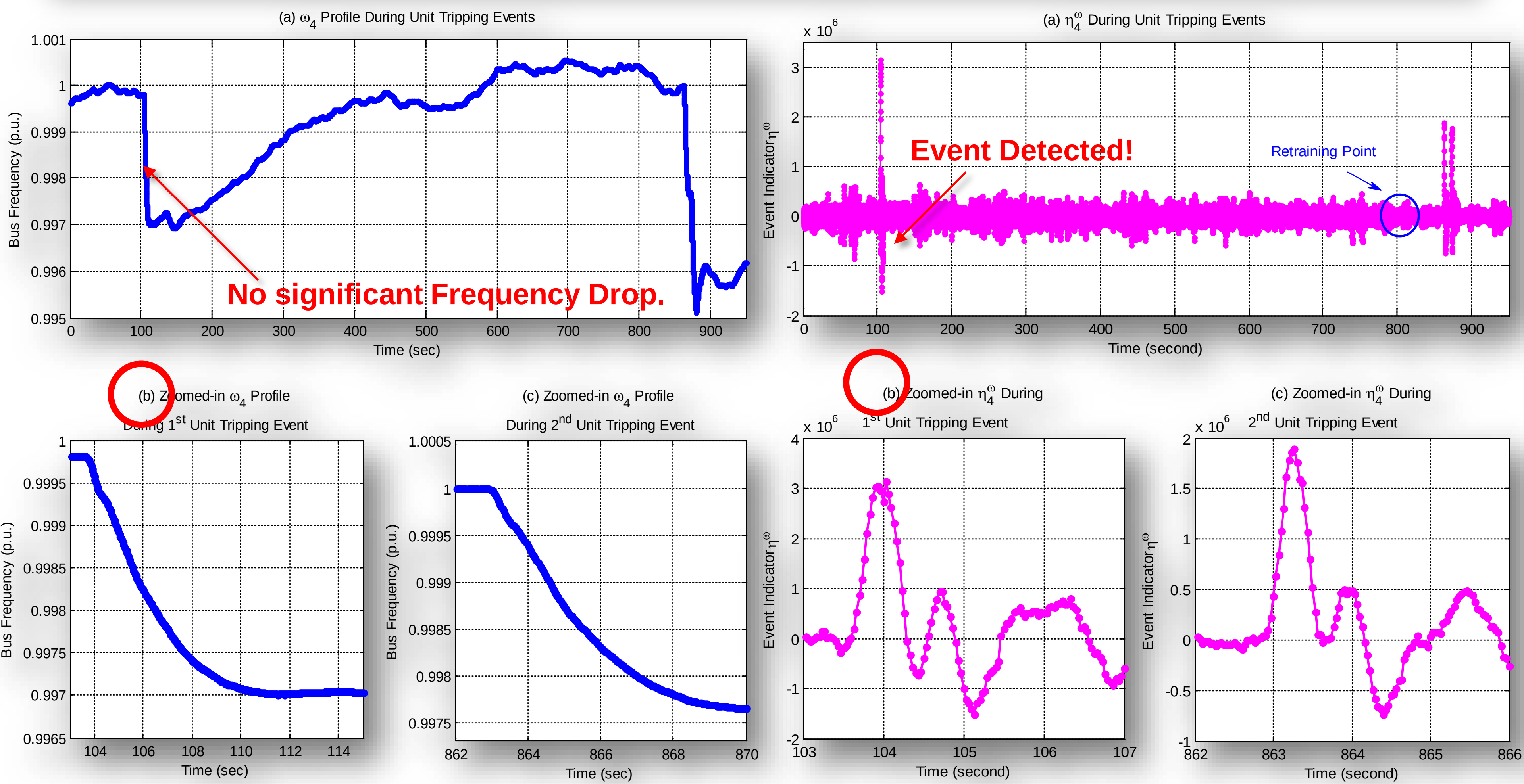
$$[c_x^{(i)} - \sum_{j=1}^{m'} v_j^{(i)} c_x^{(j)}]x[1] + [y_\varepsilon^{(i)} - \sum_{j=1}^{m'} v_j^{(i)} y_\varepsilon^{(j)}] + [c_u^{(i)} - \sum_{j=1}^{m'} v_j^{(i)} c_u^{(j)}]U_0$$
$$= \Delta c_x x[1] + \Delta y_\varepsilon + \Delta c_u U_0 \approx 0.$$

- U_0 and x[1] can be theoretically calculated by TRAINING data.
- Any changes in control inputs and initial conditions will lead to large prediction error.
- If system topology changes, Δc_x and Δc_u will change, resulting in a large prediction error.

- [6] L. Xie, Y. Chen, and P. R. Kumar, “Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis,” *IEEE Tran. Power Systems*, 2014.

Case Study 1: Unit Tripping in Texas

Number of PMUs = 7; Number of unit tripping events = 2; Sampling rate = 30 Hz.

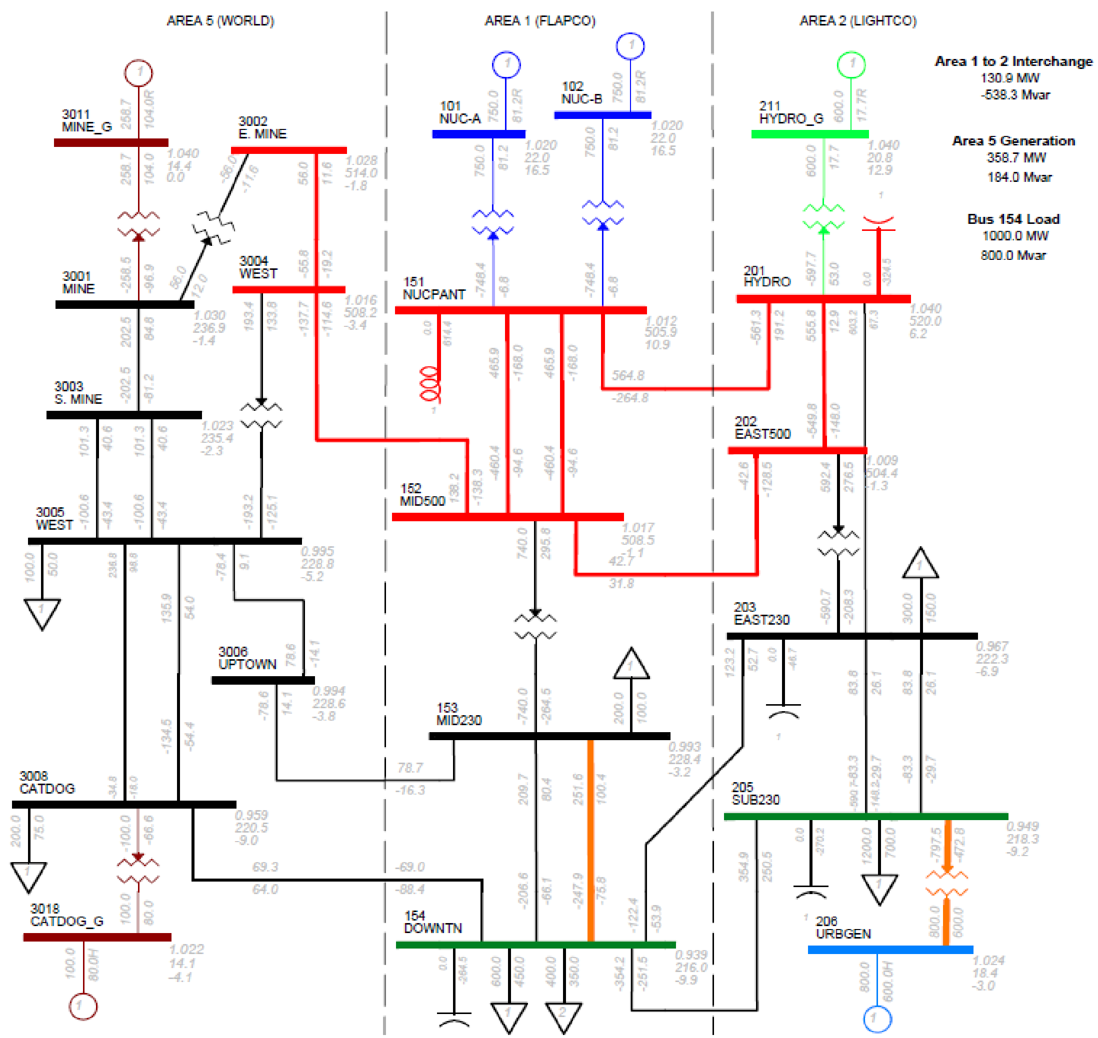


Frequency Profile. **Event Indicator Profile.**

- [6] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis," *IEEE Tran. Power Systems*, 2014.

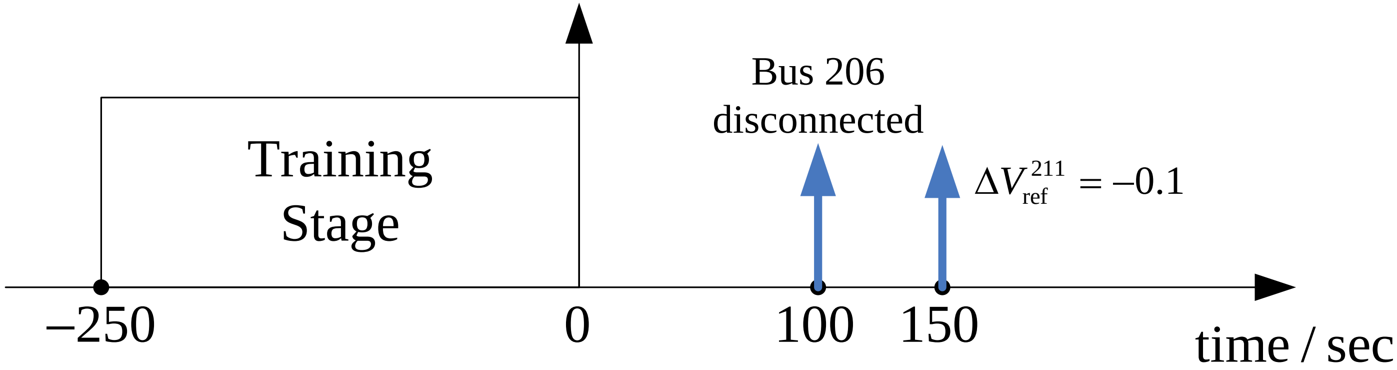
Case Study 2: Synthetic Networks

- 23-bus system
- 23 PMUs.
- Outputs of PMUs: *ω, V.*



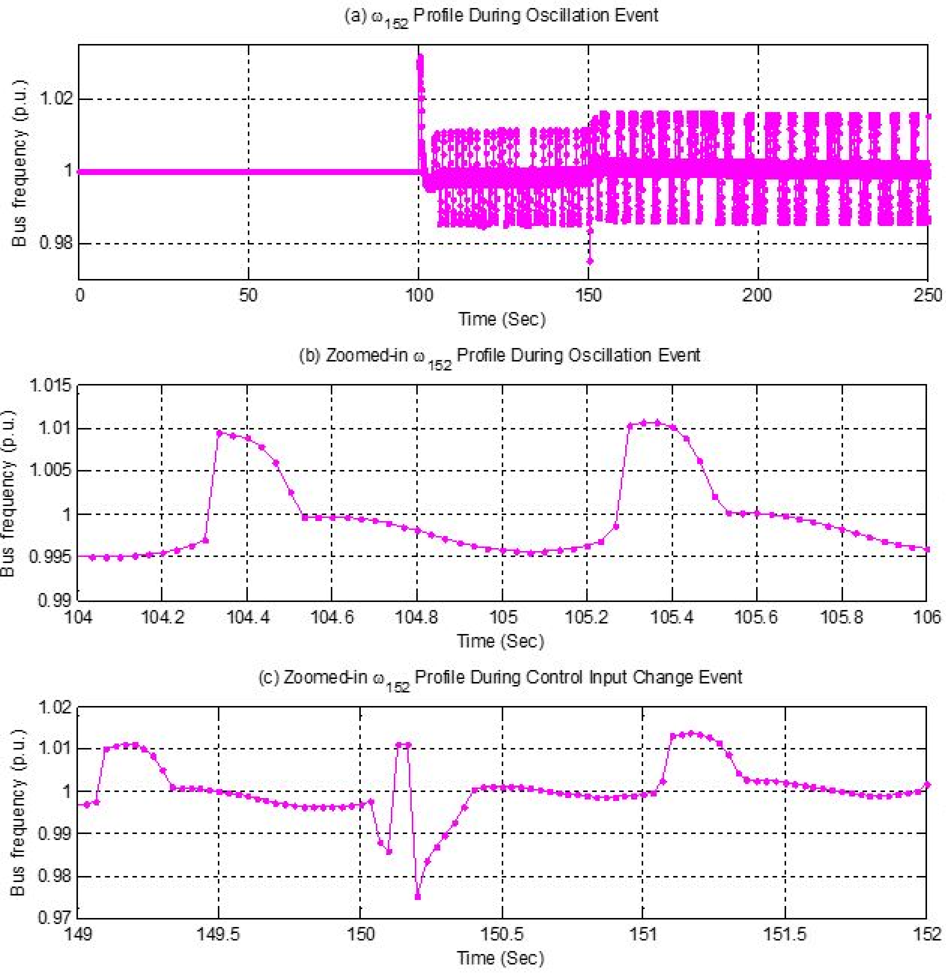
- Siemens, “PSS/E 30.2 program operational manual,” 2009.

Oscillation Event

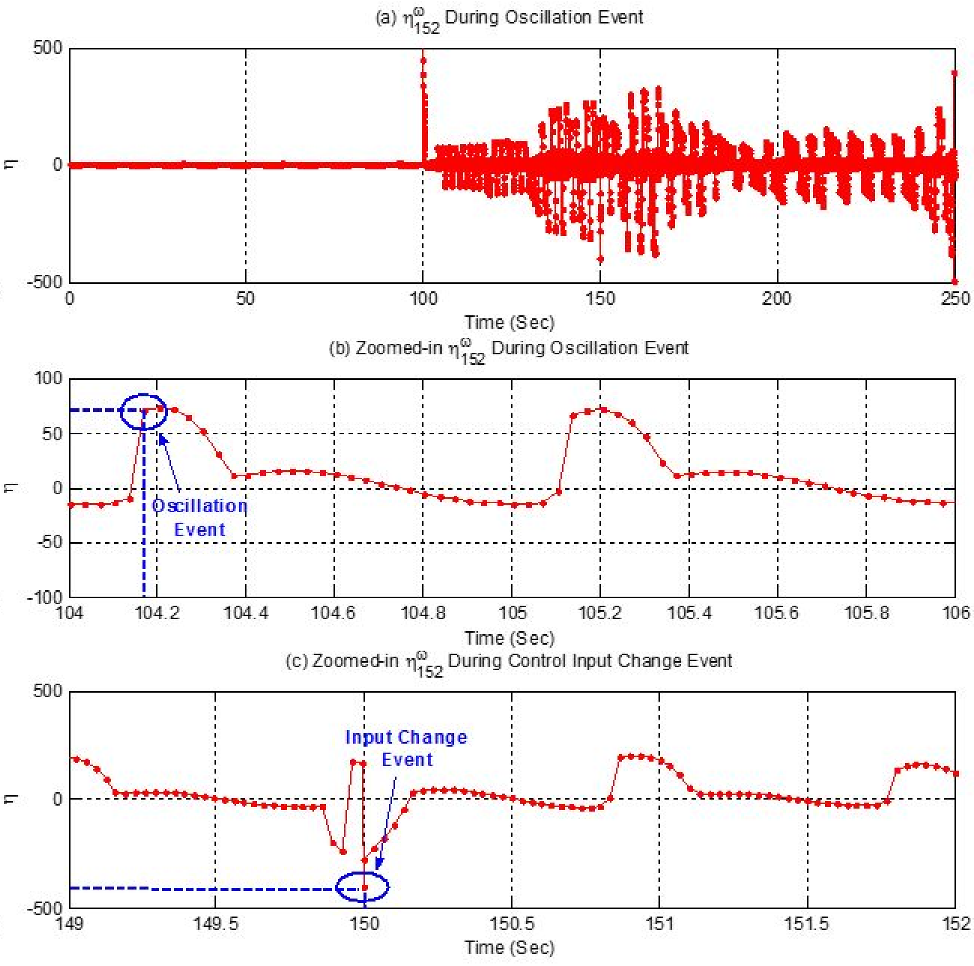


Time	Sampling Points	Event
0-100s	1-3000	Normal Condition
100.03-150s	3001-45000	Bus Disconnection (206)
150.03-250s	4501-7500	Voltage set point changes (211)

Early Event Detection



w152 **profile.**



η_{152}^{ω} **during line tripping event.**

Potential Benefits of The Algorithm

- How EARLY is the proposed algorithm?

  Proposed Method: potentially within a few samples (<0.1 seconds)

- Most Oscillation monitoring system (OMS) needs 10 sec to detect the oscillation.

- No system topology, no system model.

- Ongoing work: event *classification* and *localization*.

- [6] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality Reduction of Synchrophasor Data for Early Event Detection: Linearized Analysis," *IEEE Tran. Power Systems*, 2014.

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- **Introduction**
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- **Part II: Real-Time Detection of Low-Quality PMU Measurements**
- **Concluding Remarks**

Motivation: PMU Data Quality Problems

Current Practice

- PMU-based decision making tools require accurate PMU data for reliable analysis.
- PMU data has **higher sampling rate** and accuracy requirement.
- Typical PMU bad data ratio in California ISO ranges from **10% to 17%** (in 2011) [5].

Critical Needs

- Urgent need to develop **scalable, real-time methods** to monitor and improve PMU data quality.
- **Conventional** bad data detection **algorithms** are rendered **ineffective**, novel algorithms are needed.

- [5] California ISO, "Five year synchrophasor plan," California ISO, *Tech. Rep.*, Nov 2011.

Current Approaches for PMU Bad Data Detection

Model-Based Approach

- **Traditional WLS state estimation: based on measurement residuals and Chi-squares test [11].**
- **PMU-based state estimator: detect phasor angle bias and current magnitude scaling problems [2].**
- **Kalman-filter-based approach: detect low-quality PMU data [3].**

- **Traditional Chi-squares test approach may not be effective when multiple low-quality measurements are presented.**
- **Model-based approaches require system parameter and topology information.**
- **Model-based approaches require converged state estimation results.**

- [2] S. Ghiocel, J. Chow, et al. "Phasor-measurement-based state estimation for synchrophasor data quality improvement and power transfer interface monitoring," *IEEE Tran. Power Systems*, 2014.
- [3] K. D. Jones, A. Pal, and J. S. Thorp, “Methodology for performing synchrophasor data conditioning and validation,” *IEEE Tran. Power Systems*, May 2015.
- [11] A. Abur, and A.G. Exposito. *Power system state estimation: theory and implementation*. CRC press, 2004.

Current Approaches for PMU Bad Data Detection

Data-Driven Approach

- Low-rank matrix factorization for PMU bad data detection [4].
- Pre-defined logics & thresholds for bad data detection [1].

- Matrix factorization involves **high computational burden**.
- **Robustness of pre-defined logics** under eventful conditions.

- [1] K. Martin, "Synchrophasor data diagnostics: detection & resolution of data problems for operations and analysis", in *Electric Power Group Webinar Series*, Jan 2014.
- [4] M. Wang, J. Chow, P. Gao, X. Jiang, Y. Xia, S. Ghiocel, B. Fardanesh, G. Stefopolous, Y. Kokai, N. Saito, and M. Razanousky, "A low-rank matrix approach for the analysis of large amounts of power system synchrophasor data," in *System Sciences (HICSS), 2015 48th Hawaii International Conference on*, Jan 2015, pp. 2637–2644.

Overview of The Proposed Approach [7]

Problem Formulation

- Study *spatio-temporal correlations* among good / eventful / bad PMU data.
- Formulate bad PMU data as *spatio-temporal outliers* among other data.
- Apply *density-based outlier detection* technique to detect bad PMU data.

Online PMU Bad Data Detection Algorithm

Key Advantages:

- Online bad data detection.
- Fast without convergence issues.
- Data-driven algorithm.
- Operate under both normal and fault-on operating conditions.

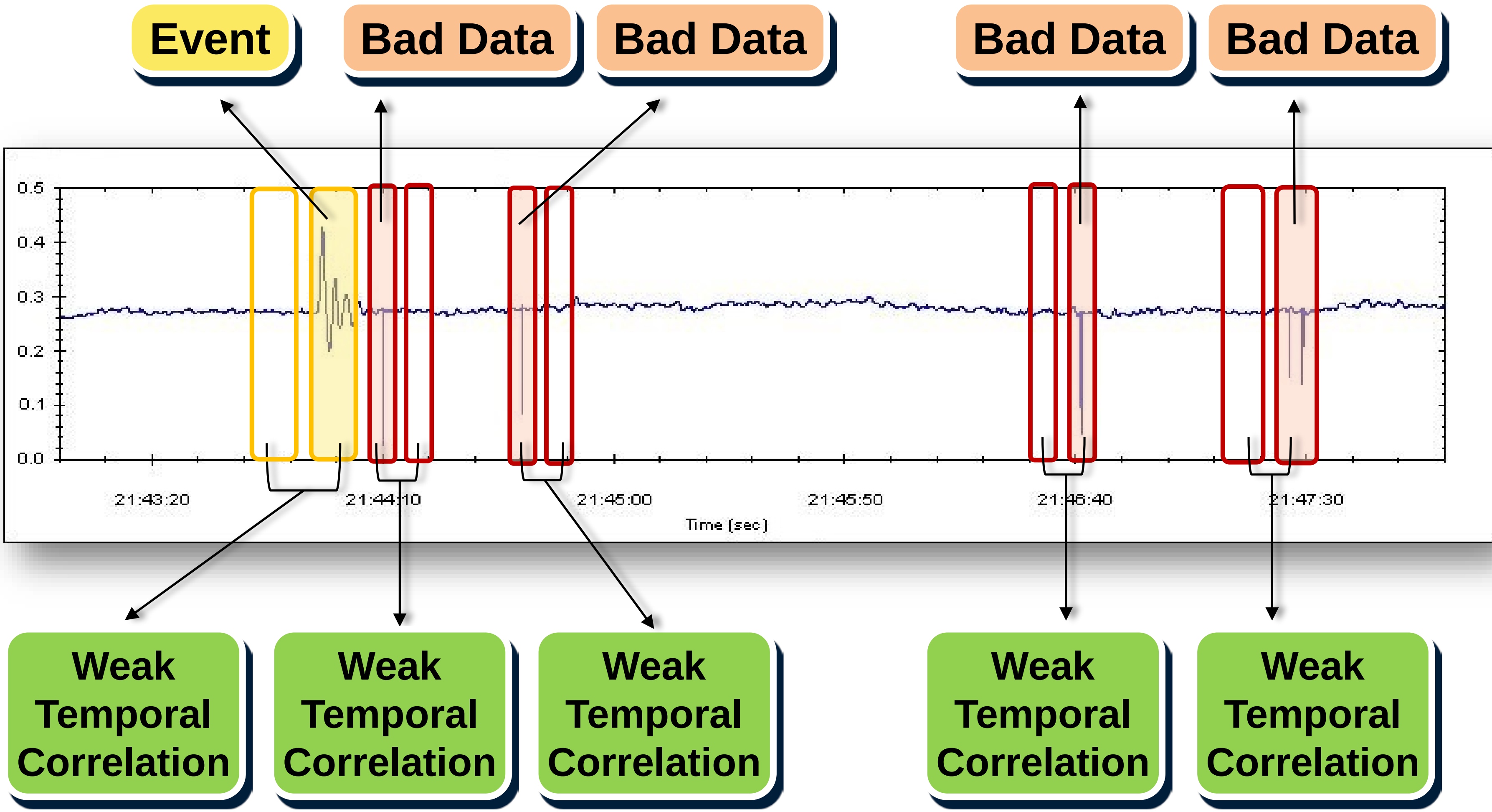
Detect Various Types of Bad Data:

- High communication noise.
- Missing data (communication loss).
- Data spikes (gross error / GPS error).
- Un-updated data.
- *False data injection (cyber attacks)*.

- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.
- [12] M. Wu and L. Xie, "Online Detection of False Data Injection Attacks to Synchrophasor Measurements: A Data-Driven Approach," *System Sciences (HICSS), 2017 50th Hawaii International Conference on*, Jan 2017.

Good Data VS Eventful Data VS Bad Data

Phase Angle Measured by A Western System PMU for A Recent Brake Test Event



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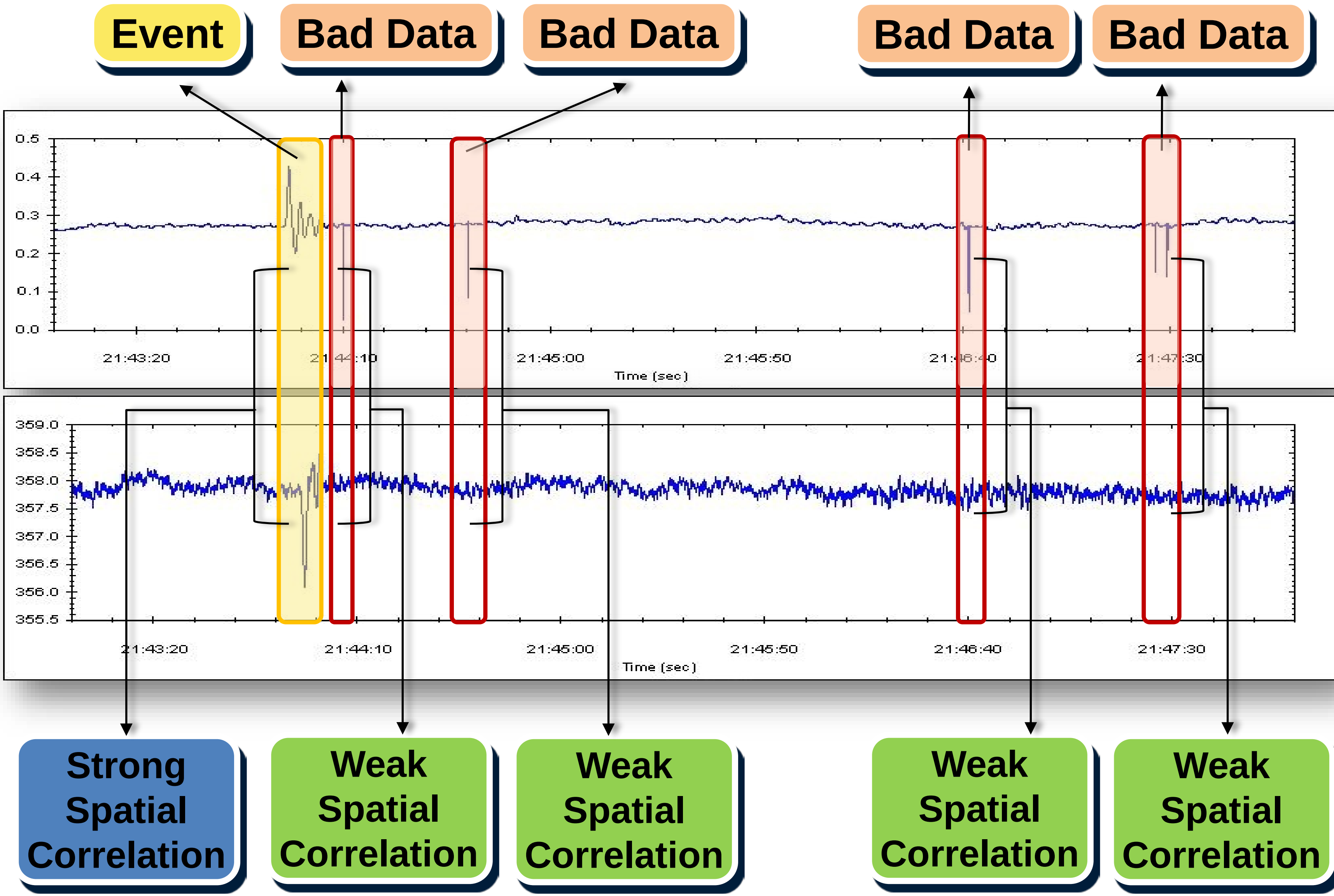


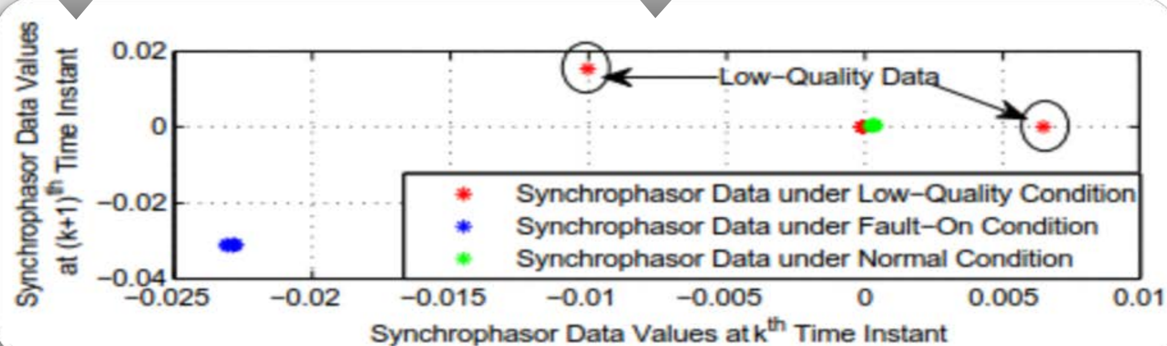
- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.

Features of Good / Eventful / Bad Data

Criteria: Good Data VS Eventful Data VS Bad Data

- **Good Data: strong spatio-temporal correlations with its neighbors.**
- **Eventful Data: weak temporal but strong spatial correlations with its neighbors.**
- **Bad Data/Attacked Data: *weak spatio-temporal correlations* with its neighbors.**

PMU Bad Data: Spatio-Temporal Outlier



- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.

Quantification of Spatio-Temporal Correlations [7]

Definition of Normalized Standard Deviation

- **Normalized standard deviation:**

$$\sigma_i^{Norm}(k) = \frac{\sigma_i(k)}{\frac{\sum_{t=1}^{t=k-1} \sigma_i(t)\chi_C(M_i(t))}{\sum_{t=1}^{t=k-1} \chi_C(M_i(t))}}$$

$$\chi_C(M_i(t)) = \begin{cases} 1 & (M_i(t) \in C) \\ 0 & (M_i(t) \notin C) \end{cases}$$

- **Explanation:**

✓ **Standard deviation of PMU curve obtained from i^{th} PMU channel at k^{th} time window, normalized by the average standard deviation of the historical clean data of the same PMU channel.**

Spatio-Temporal Correlation Metrics (Distance Function)

- **For high-variance bad data:**

$$f_H(i,j) = \left|\sigma_i^{Norm} - \sigma_j^{Norm}\right|$$

✓ **High-variance bad data: data spikes, data loss, high noise, false data injections, etc.**

- **For low-variance bad data:**

$$f_L(i,j) = max\left(\left|\frac{\sigma_i^{Norm}}{\sigma_j^{Norm}}\right|, \left|\frac{\sigma_j^{Norm}}{\sigma_i^{Norm}}\right|\right)$$

✓ **Low-variance bad data: un-updated data, etc.**

- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.

Online Detection of Low-Quality PMU Data [10]

Spatio-Temporal Correlation Metrics (Distance Function)

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✓ **Low-variance bad data: un-updated data, etc.**

Density-Based Local Outlier Detection

- **Local Reachability Density:**

$$lrd_{MinPts}(p) = 1/\left(\frac{\sum_{o\in N_{MinPts}(p)} reach-dist_{MinPts}(p,o)}{|N_{MinPts}(p)|}\right)$$

- **Local Outlier Factor [12]:**

$$LOF_{MinPts}(p) = \frac{\sum_{o\in N_{MinPts}(p)} \frac{lrd_{MinPts}(o)}{lrd_{MinPts}(p)}}{|N_{MinPts}(p)|}$$

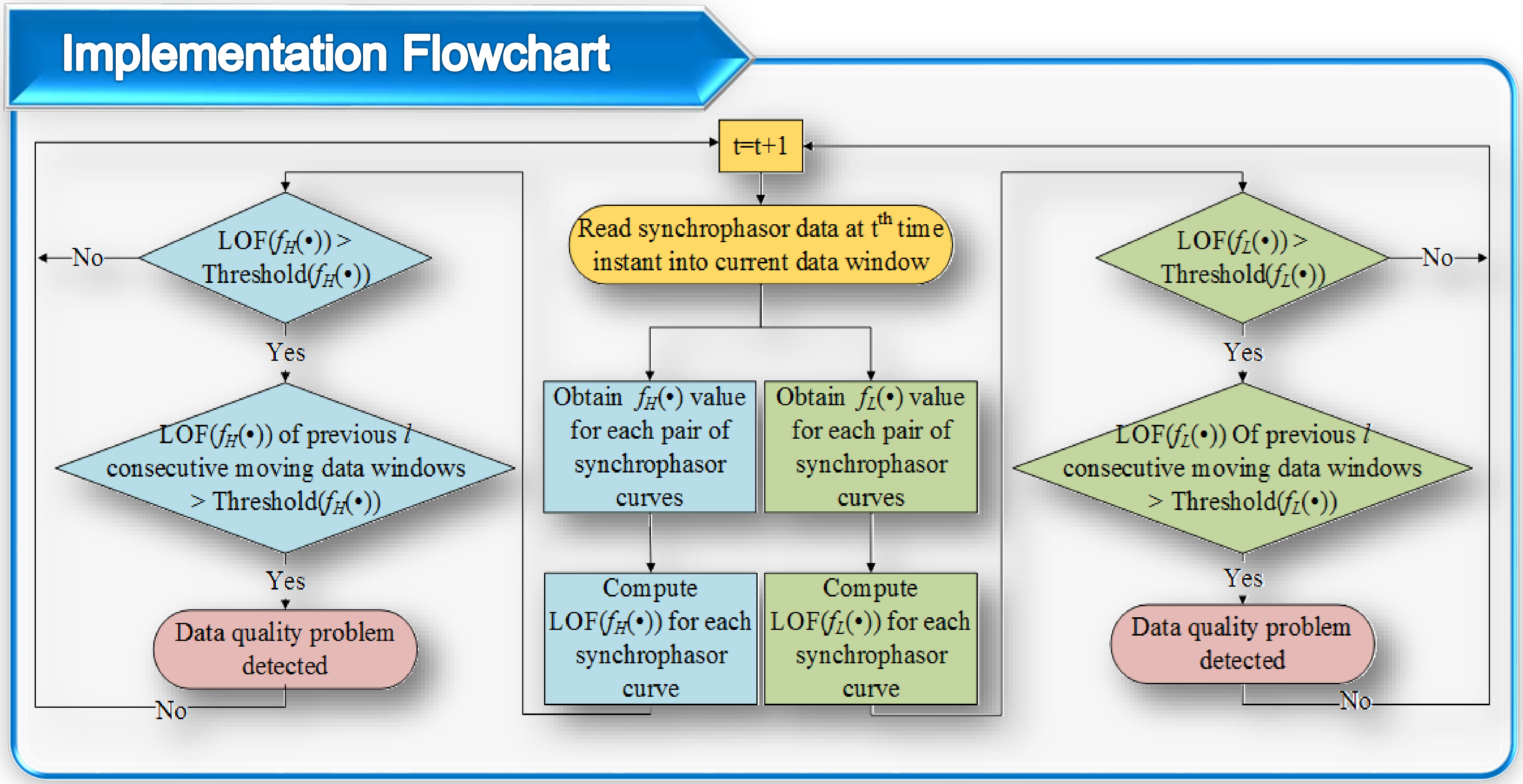
- **Bad Data Detection:**

✓ **LOF(p) >> 1: p contains bad data.**

✓ **LOF(p) ≈ 1: p contains good data only.**

- [10] Breunig, Markus M., et al. "LOF: identifying density-based local outliers." *ACM sigmod record*. Vol. 29. No. 2. ACM, 2000.

Online Detection of Low-Quality PMU Data [7]



- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.

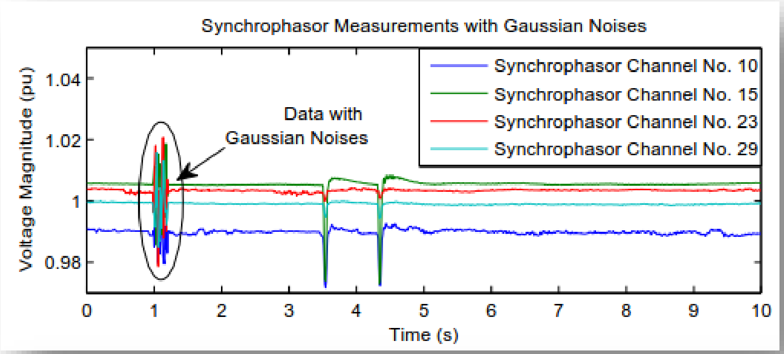
Numerical Results – High Sensing Noise

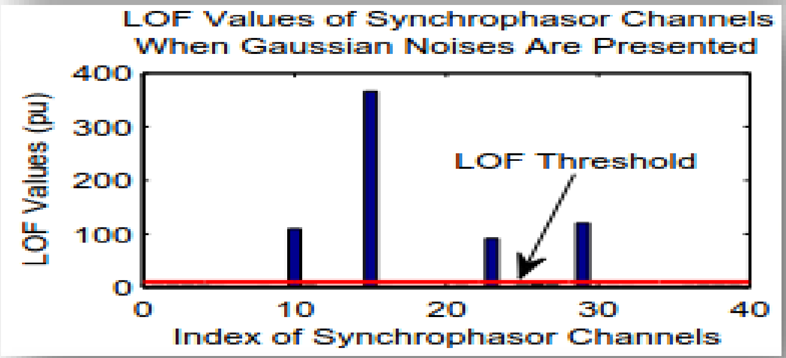
Test Case Description

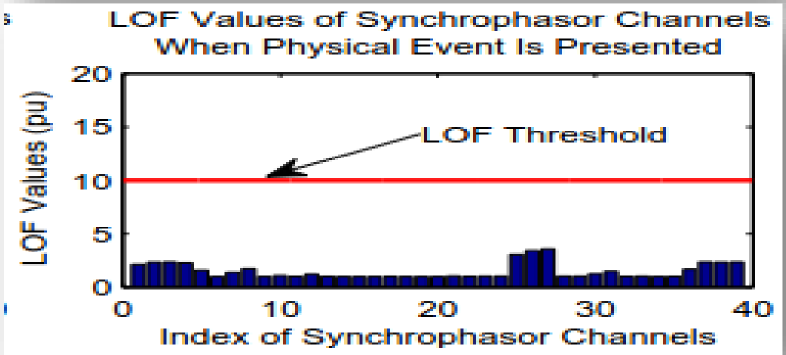
- 39 real-world PMU voltage magnitude data curves.
- PMU No. 10, 15, 23, 29 contain Gaussian noises (SNR = 40 db) lasting from 1s to 1.2s.
- Line tripping fault is presented around 4s.

Numerical Results Description

- All the 4 bad data segments are detected.
- System event does not cause false alarms.
- Detection delay is less than 0.19s.
- Computation time for each data window is 0.0376s.







- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.

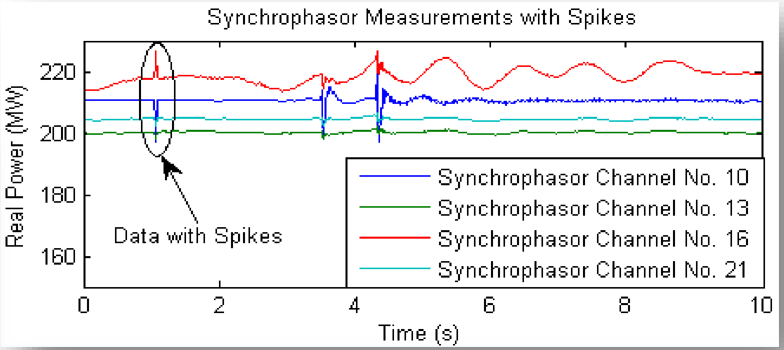
Numerical Results – Data Spikes

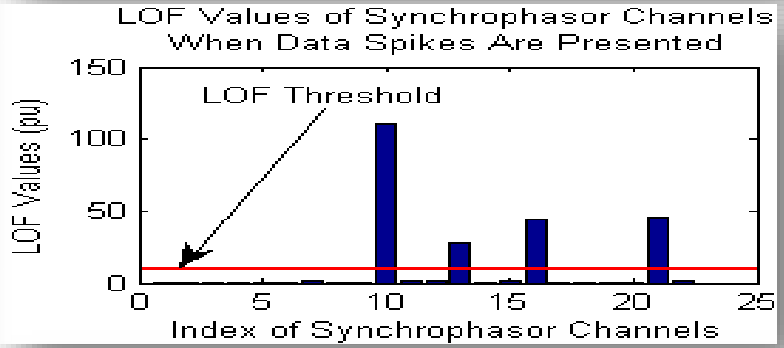
Test Case Description

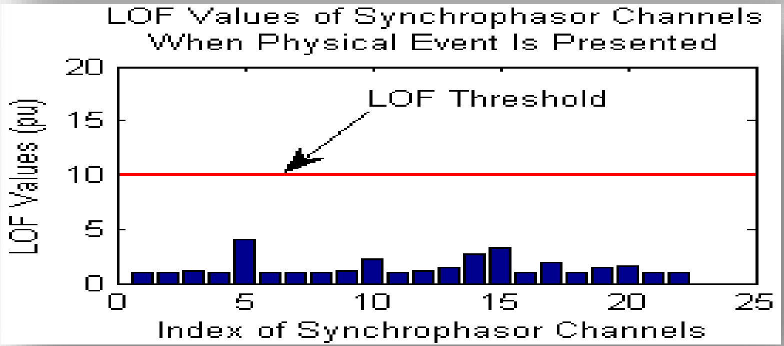
- **22 real-world PMU real power data curves.**
- **PMU No. 10, 13, 16, 21 contain data spikes lasting from 1.05s to 1.1s.**
- **Line tripping fault is presented around 4s.**

Numerical Results Description

- **All the 4 bad data segments are detected.**
- **System event does not cause false alarms.**
- **Detection delay is less than 0.18s.**
- **Computation time for each data window is 0.0197s.**







- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.

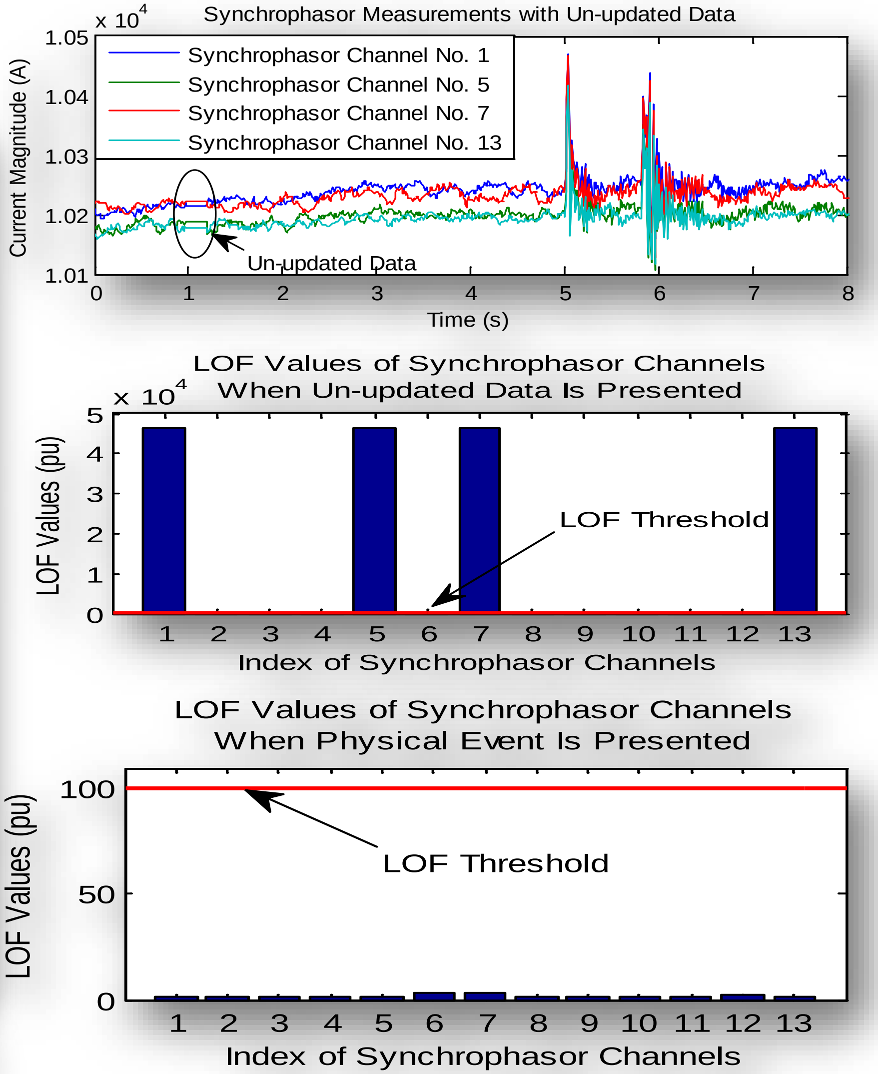
Numerical Results – Un-updated Data

Test Case Description

- **13 real-world PMU current magnitude data curves.**
- **PMU No. 1, 5, 7, 13 contain un-updated data lasting from 1s to 1.2s.**
- **Line tripping fault is presented around 4s.**

Numerical Results Description

- **All the 4 bad data segments are detected.**
- **System event does not cause false alarms.**
- **Detection delay is less than 0.18s.**
- **Computation time for each data window is 0.0115s.**



- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.

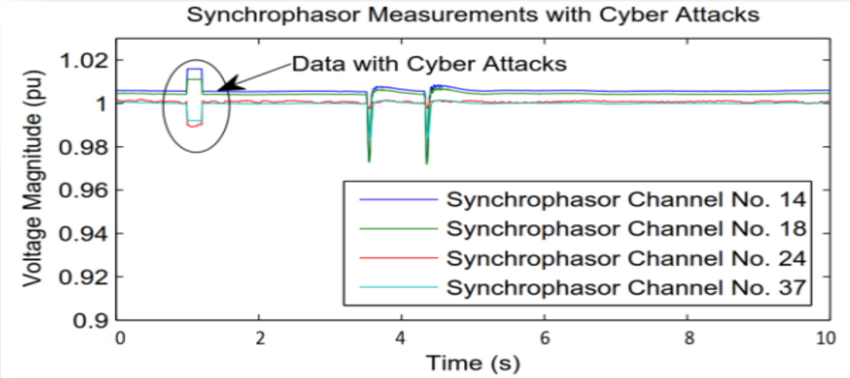
Numerical Results – False Data Injections

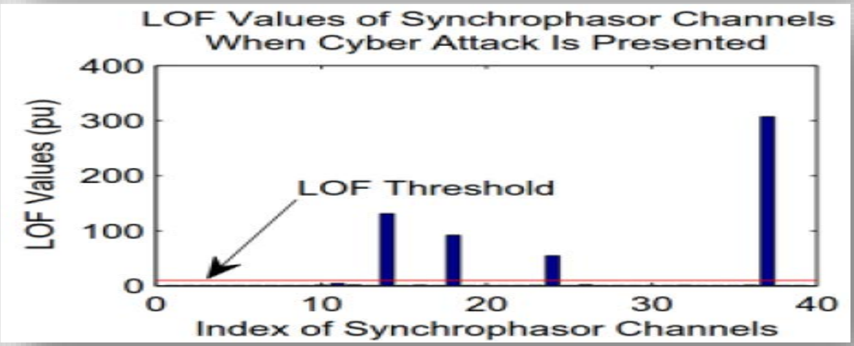
Test Case Description

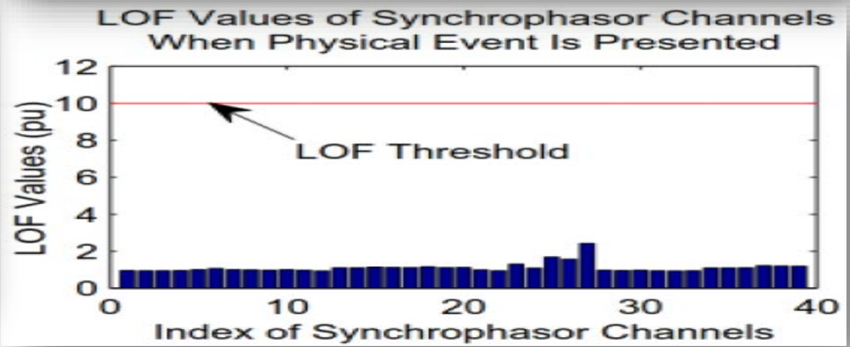
- 39 real-world PMU voltage magnitude data curves.
- PMU No. 14, 18, 24, 37 contain false data injections lasting from 1s to 1.2s.
- Line tripping fault is presented around 4s.

Numerical Results Description

- All the 4 false data injections are detected.
- System event does not cause false alarms.
- Detection delay is less than 0.19s.
- Computation time for each data window is 0.040s.







- [12] M. Wu and L. Xie, "Online Detection of False Data Injection Attacks to Synchrophasor Measurements: A Data-Driven Approach," *System Sciences (HICSS), 2017 50th Hawaii International Conference on*, Jan 2017.

Real-Time Detection of Low-Quality PMU Data

Conclusions

<u>**An approach for PMU low-quality data detection is proposed:**</u>

- **It is purely data-driven, without involving any knowledge on network parameters or topology, which avoids the impact of incorrect parameter/topology information on the identification results.**
- **It encounters no convergence issues and has fast computation performance, which is desirable for online application.**
- **It is suitable for identifying low-quality data in PMU outputs under both normal and eventful operating conditions.**

- [7] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.

Presentation Outline

- **Introduction**
- **Part I: PMU Dimensionality Reduction & Early Event Detection**
- **Part II: Real-Time Detection of Low-Quality PMU Measurements**
- **Concluding Remarks**

Concluding Remarks

Our Research

- ***Dimensionality reduction*** **of PMU data.**
- **Online *data driven* PMU-based early event detection.**
- **Real-time *data-driven* PMU bad data detection.**

PMU Challenges

- **High dimensionality: Tennessee Valley Authority (TVA) 120 PMUs produces 36GB data per day.**
- **State-of-the-art: primarily offline, post-event analysis.**
- **High Bad Data Ratio: Typical PMU bad data ratio in California ISO ranges from 10% to 17% (in 2011).**

Ongoing Research and Future Challenges

- How to integrate real-time *physical model-based* and *data-driven* monitoring analytics?
- How to analyze the *root-cause* and *correct* low-quality data?
- How to *close the loop (control)* around real-time streaming PMU with the presence of bad as well as cyber-attacked data?
- Would PMU be needed at *distribution level*, for what purpose [13][14]?
- Many other possibilities…

- [13] Y. Zhang and L. Xie. "Online dynamic security assessment of microgrid interconnections in smart distribution systems." *IEEE Transactions on Power Systems*, Vol. 30. no. 6, pp. 3246-3254, Nov 2015
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- [13] Y. Zhang and L. Xie. "Online dynamic security assessment of microgrid interconnections in smart distribution systems." IEEE Transactions on Power Systems 30.6 (2015): 3246-3254.
- [14] Y. Zhang and L. Xie, "A Transient Stability Assessment Framework in Power Electronic-Interfaced Distribution Systems," in *IEEE Transactions on Power Systems*, vol. 31, no. 6, pp. 5106-5114, Nov. 2016.

Questions?

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