Real-Time Model-Free Detection of Low-Quality Synchrophasor Data

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Presentation Outline

1 **Introduction**

2 **Technical Approach**

3 **Case Studies**

4 **Conclusions & Future Work**

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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) [1].

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.

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

Current Approaches for PMU Bad Data Detection

Model-Based Approach

- PMU-based state estimator [2].
- Kalman-filter-based approach [3].
- Require system parameter and topology information.
- Require converged state estimation results.

Data-Driven Approach

- Low-rank matrix factorization for PMU bad data detection [4].
- Pre-defined logics & thresholds for bad data detection [5].
- Matrix factorization involves high computational burden.
- Robustness of pre-defined logics under eventful conditions.

[2] S. Ghiocel, J. Chow, et al. "Phasor-measurement-based state estimation for synchrophasor data quality improvement and power transfer interface monitoring".
[3] K. D. Jones, A. Pal, and J. S. Thorp, "Methodology for performing synchrophasor data conditioning and validation".
[4] M. Wang, J. Chow, et al. "A low-rank matrix approach for the analysis of large amounts of power system synchrophasor data".
[5] K. Martin, "Synchrophasor data diagnostics: detection & resolution of data problems for operations and analysis".

Overview of The Proposed Approach [6]

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.
- Cyber attacks (false data injection).

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- [6] 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

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Good Data VS Eventful Data VS Bad Data

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

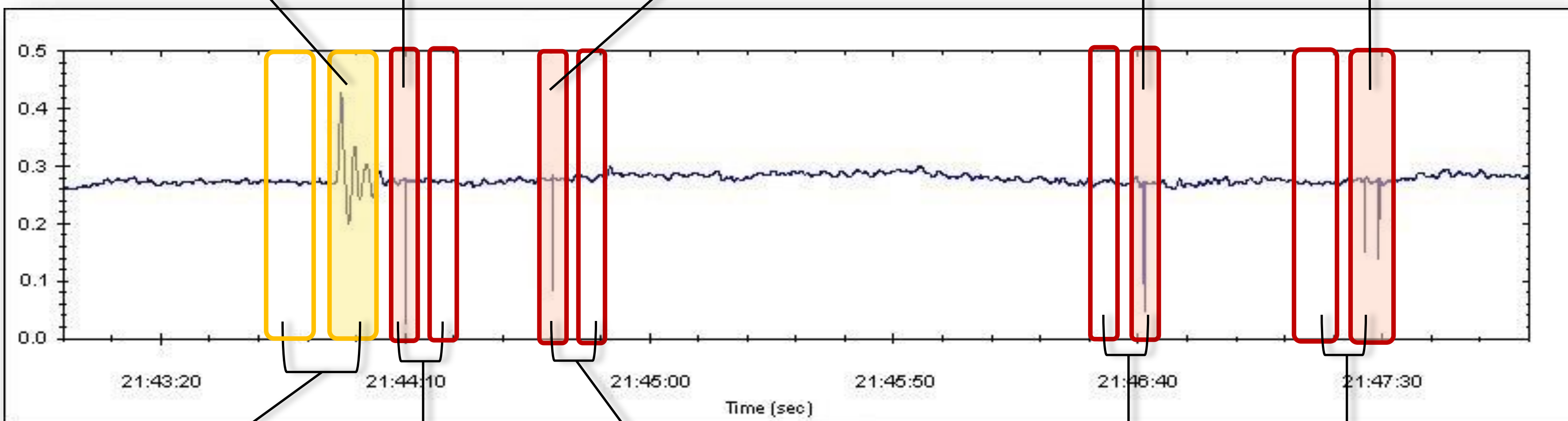
Event

Bad Data

Bad Data

Bad Data

Bad Data



Weak Temporal Correlation

Weak Temporal Correlation

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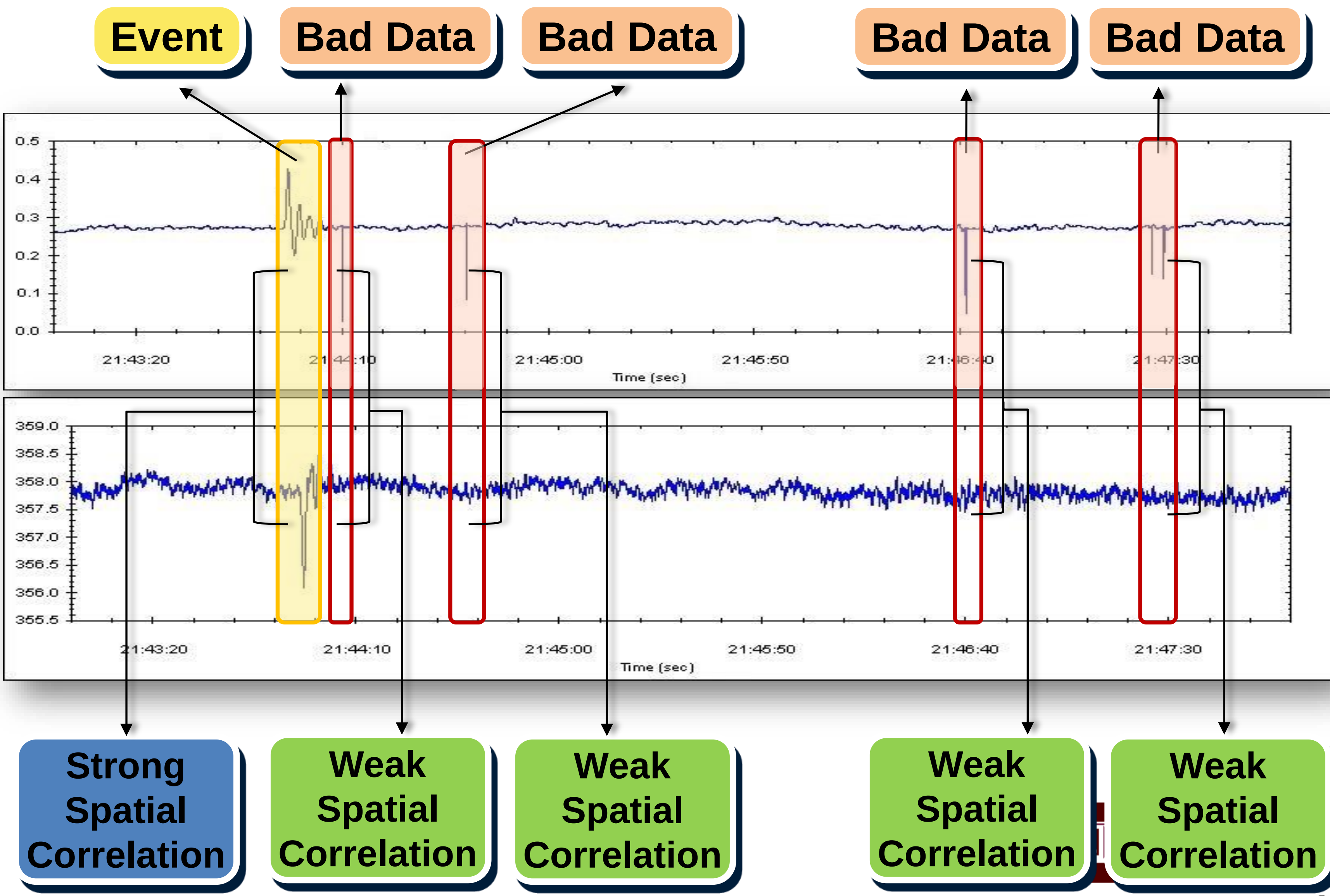
Good Data VS Eventful Data VS Bad Data

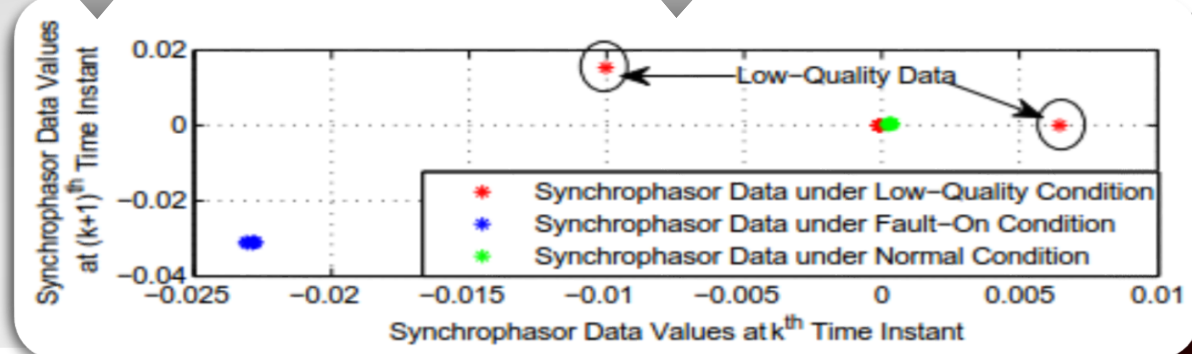


Features of Good / Eventful / Bad Data

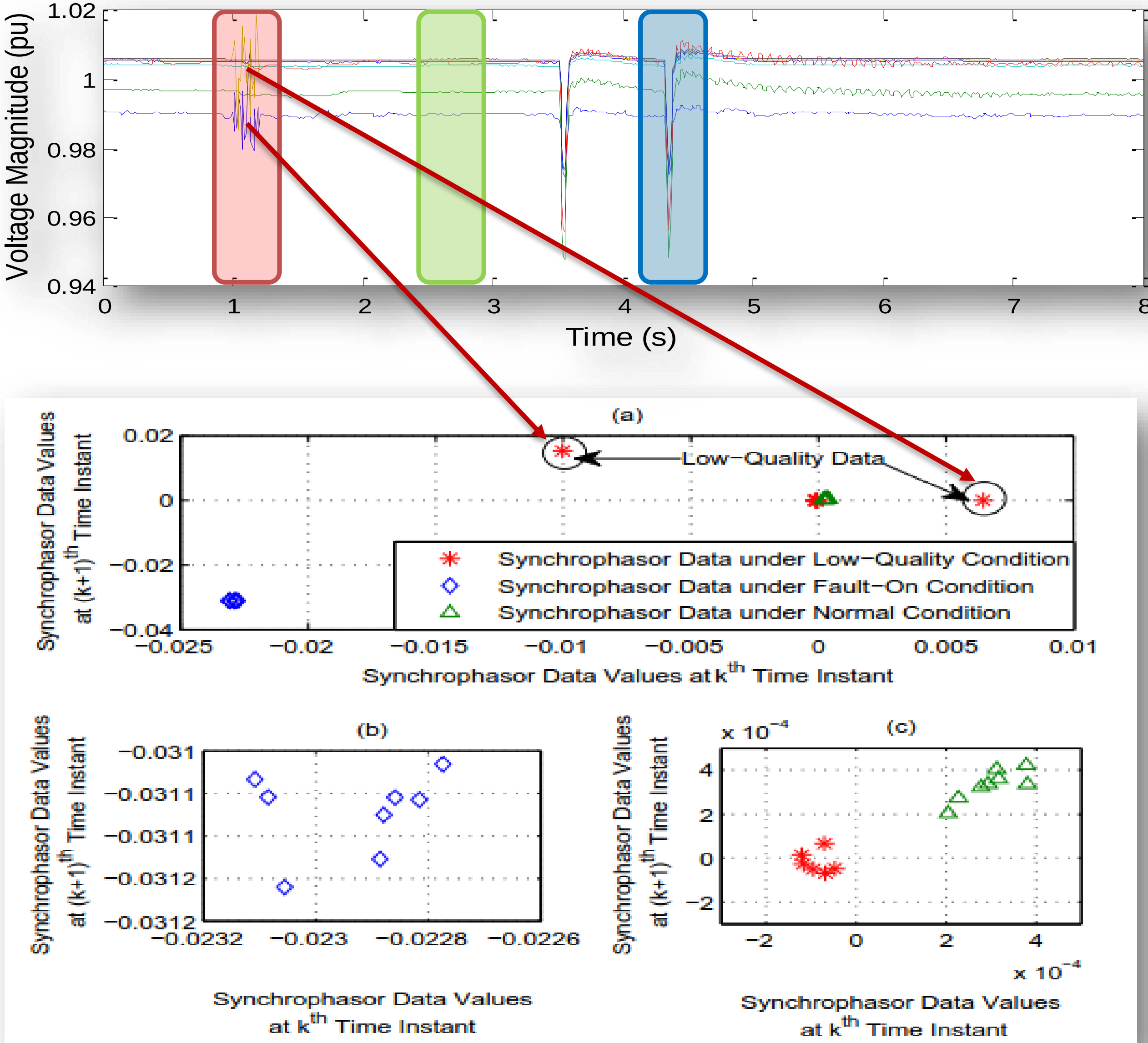
Criteria: Good Data VS Eventful Data VS Bad Data

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

PMU Bad Data: Spatio-Temporal Outlier



Example of Spatio-Temporal Correlations



- ❖ 8 PMU curves
- ❖ 3 time windows
- ❖ 2 instants / window

Map 3×8 Curves To 2D Euclidian Space

- ❖ 8 green points (normal window)
- ❖ 8 blue points (fault-on window)
- ❖ 8 red points (low-quality window)
- ❖ 2 red outliers (low-quality data)

Quantification of Spatio-Temporal Correlations [6]

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.

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Online Detection of Low-Quality PMU Data [7]

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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]:

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

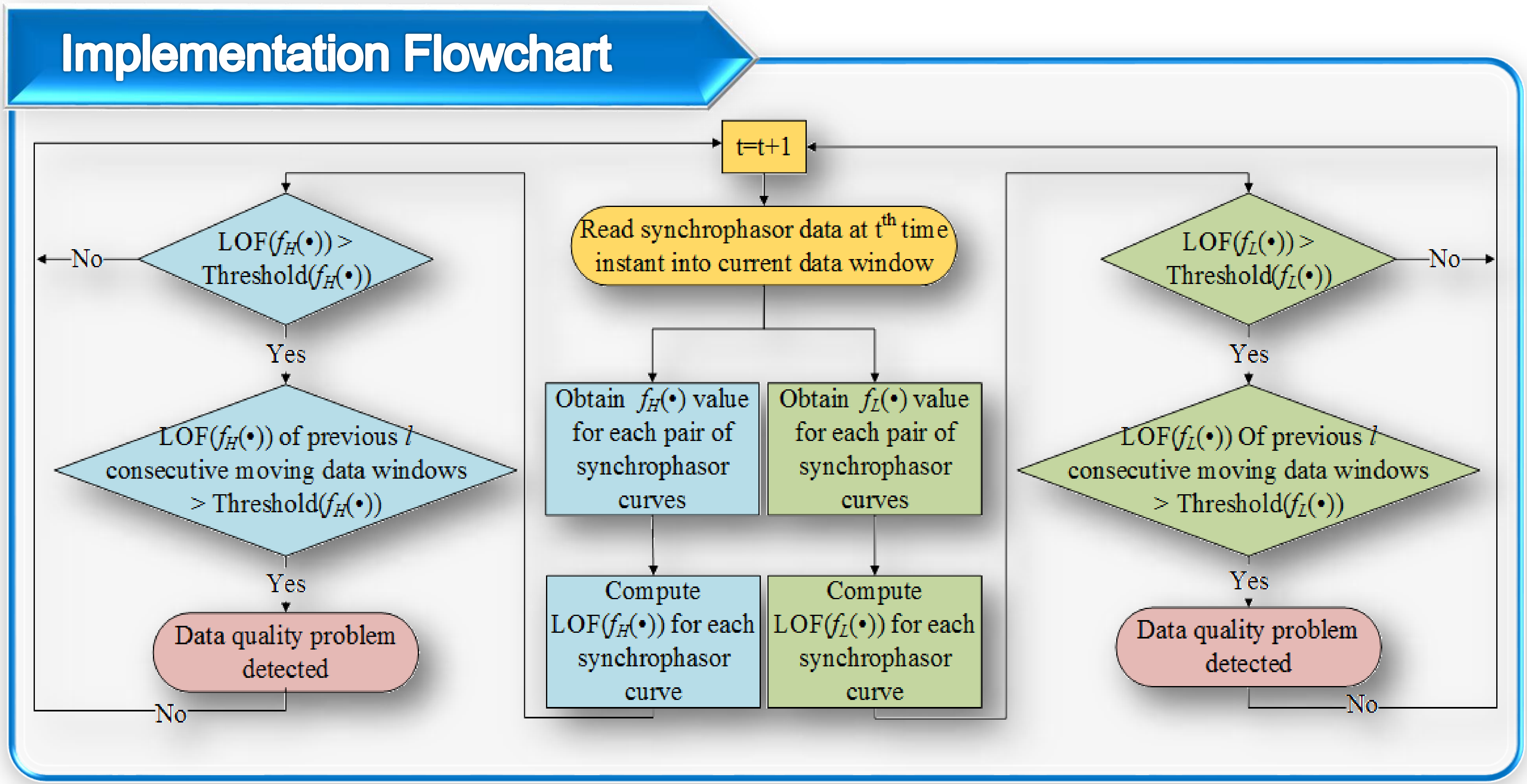
- Bad Data Detection:

✓ LOF(p) >> 1: p contains bad data.

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

- [7] 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 [6]



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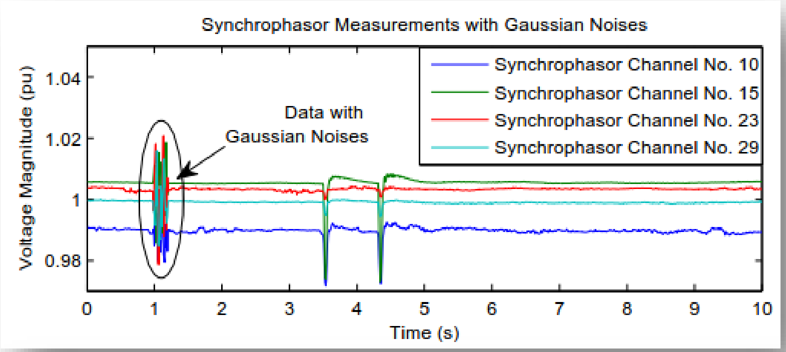
Numerical Results – High Sensing Noise

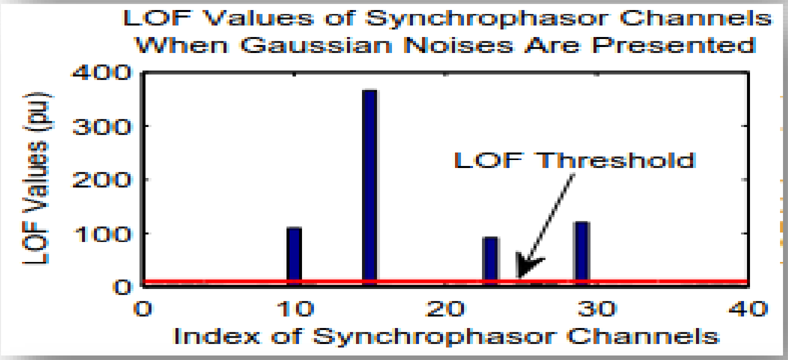
Test Case Description

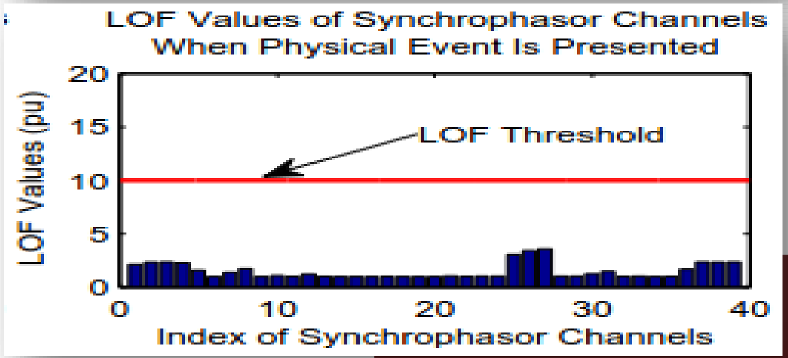
- **39 real-world PMU voltage magnitude data curves.**
- **PMU No. 10, 15, 23, 29 contain Gaussian noises (SNR = 40 db) lasting from 1s to 1.2s.**
- **Line tripping fault is presented around 4s.**

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.**







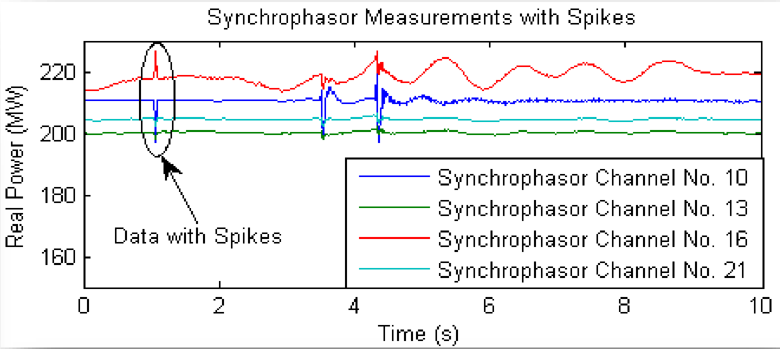
Numerical Results – Data Spikes

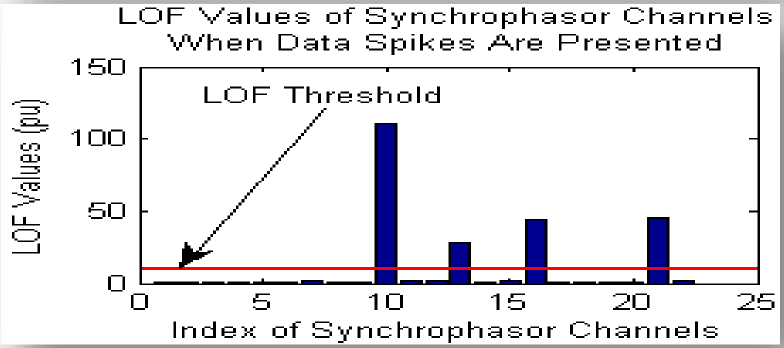
Test Case Description

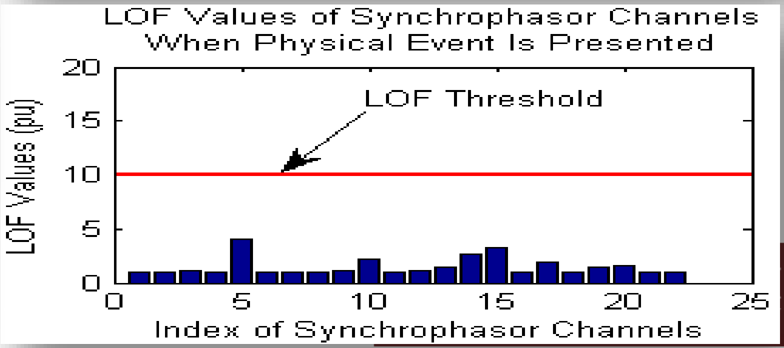
- 22 real-world PMU real power data curves.
- PMU No. 10, 13, 16, 21 contain data spikes lasting from 1.05s to 1.1s.
- Line tripping fault is presented around 4s.

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.







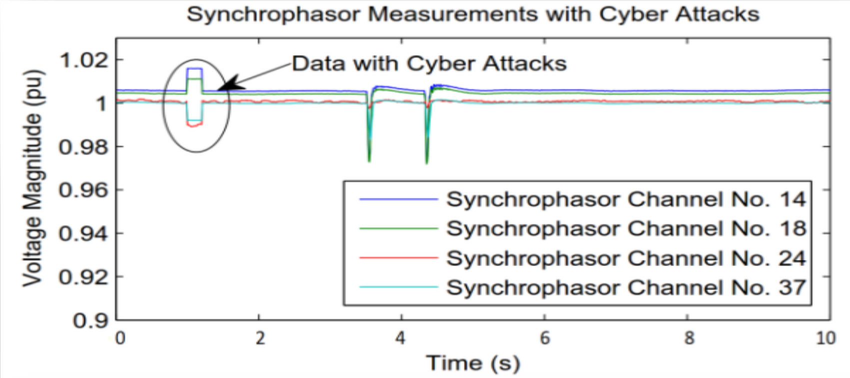
Numerical Results – False Data Injection Attacks

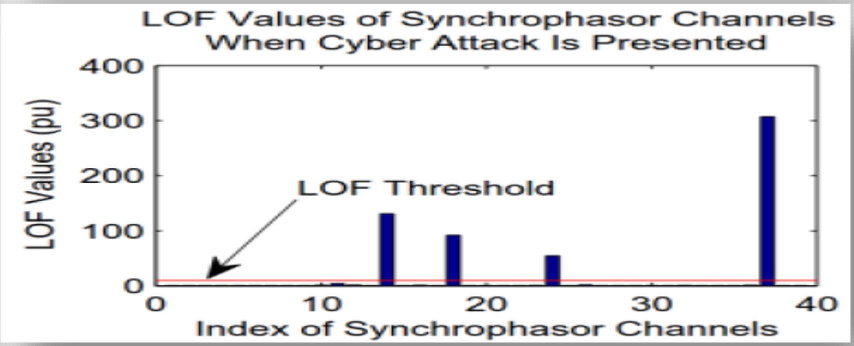
Test Case Description

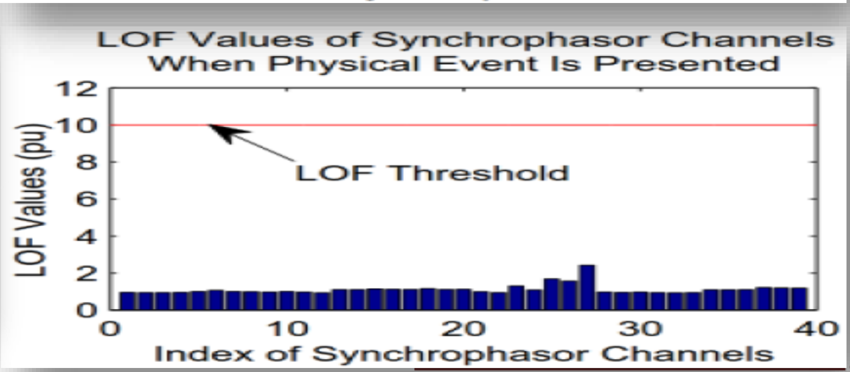
- **39 real-world PMU voltage magnitude data curves.**
- **PMU No. 14, 18, 24, 37 contain false data injections lasting from 1s to 1.2s.**
- **Line tripping fault is presented around 4s.**

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.**







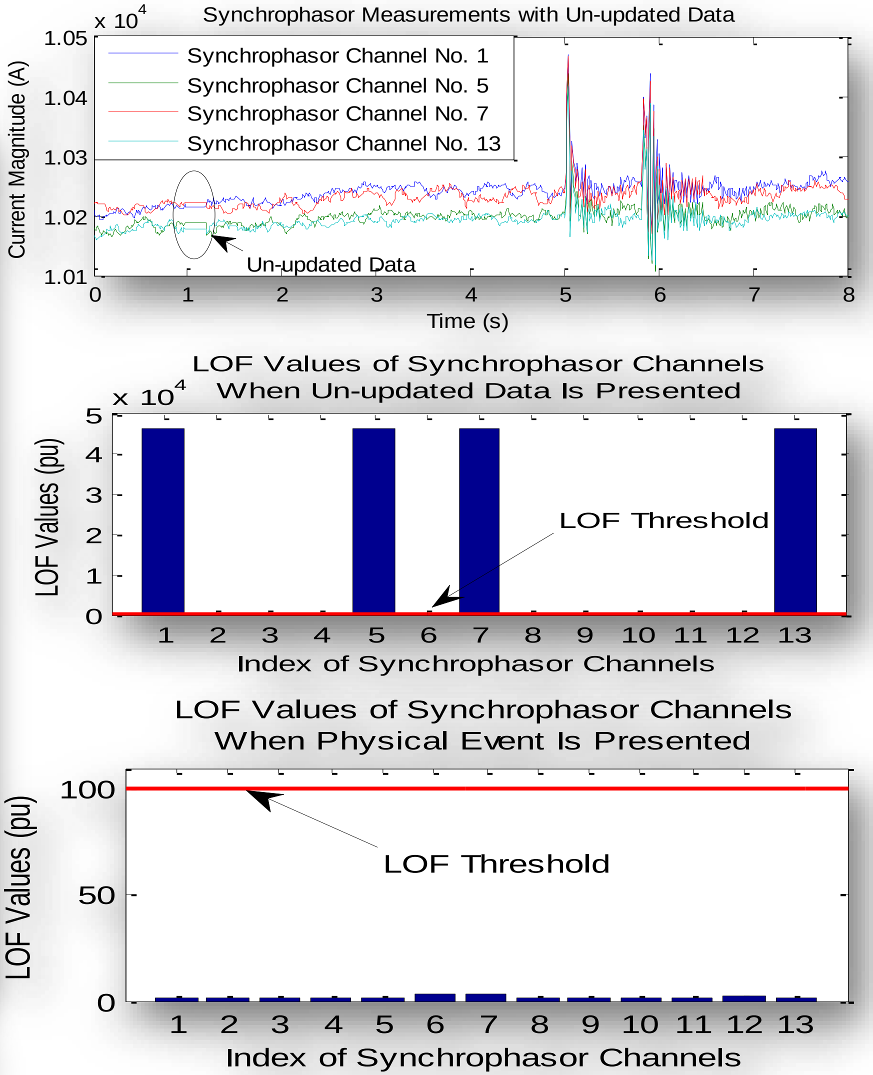
Numerical Results – Un-updated Data

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.**



Numerical Results – Different Similarity Metrics

Similarity Metric for High-Variance Bad Data

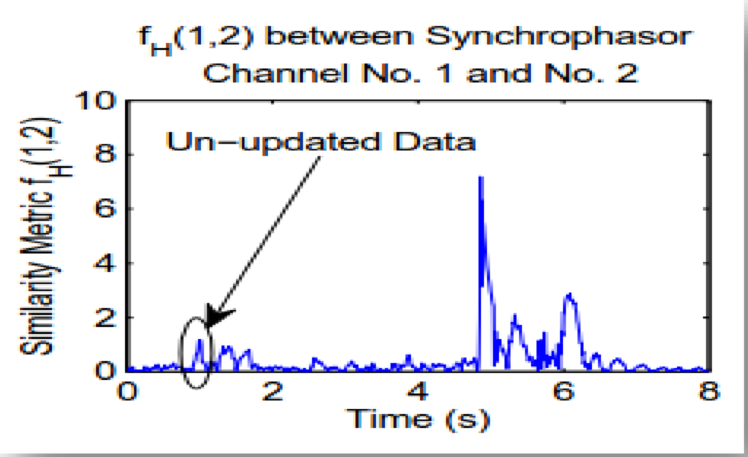
$$f_H(i,j) = \left|\sigma_i^{Norm} - \sigma_j^{Norm}\right|$$

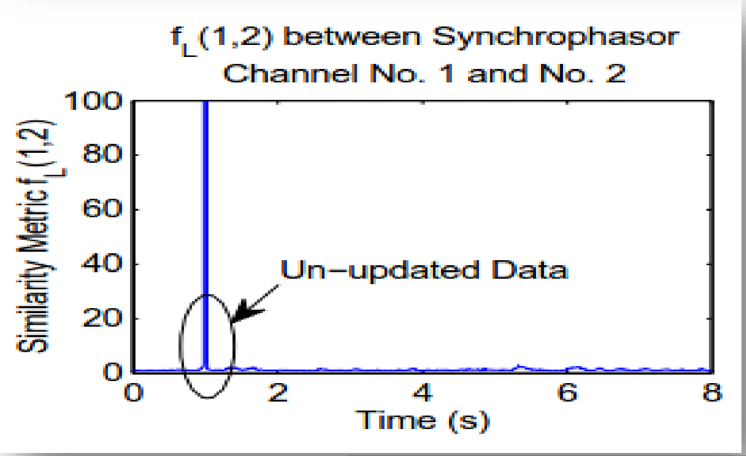
Similarity Metric for Low-Variance Bad Data

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

Performance Difference

- $f_H(i,j)$ **is more sensitive to high-variance bad data.**
- $f_L(i,j)$ **is more sensitive to low-variance bad data.**





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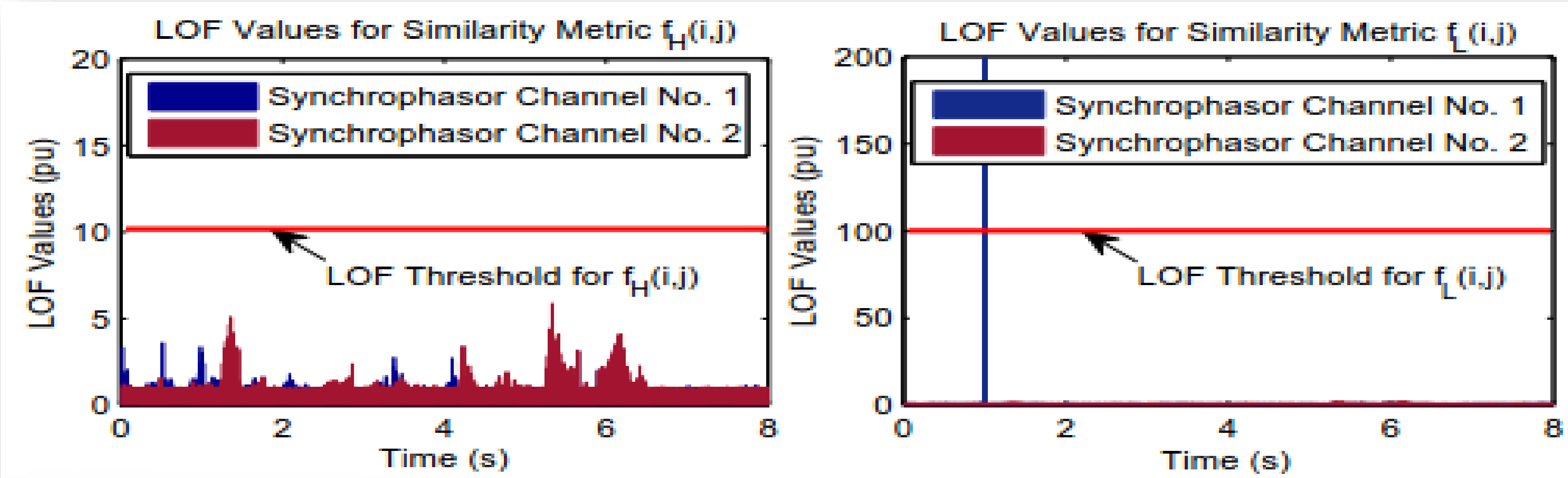

Observations

- LOF indicator based on $f_H(i,j)$ is more sensitive to ***high-variance*** bad data.
- LOF indicator based on $f_L(i,j)$ is more sensitive to ***low-variance*** bad data.

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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.

Future Work

- Identify the root cause of the low-quality PMU data.
- Propose correction mechanism for the low-quality PMU data.

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References

References

- [1] California ISO, “Five year synchrophasor plan,” California ISO, *Tech. Rep.*, Nov 2011.
- [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.
- [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.
- [5] K. Martin, “Synchrophasor data diagnostics: detection & resolution of data problems for operations and analysis”, in *Electric Power Group Webinar Series*, Jan 2014.
- [6] M. Wu, and Le Xie. Online Detection of Low-Quality Synchrophasor Measurements: A Data-Driven Approach. *IEEE Transactions on Power Systems*. Accepted, to appear.
- [7] Breunig, Markus M., et al. "LOF: identifying density-based local outliers." *ACM sigmod record*. Vol. 29. No. 2. ACM, 2000.

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