Online Bad Data Detection for Synchrophasor Systems via Spatio-temporal Correlations

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Motivation of This Work

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.

Current Work 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 [1].
- Matrix factorization involves high computational burden.
- Robustness of pre-defined logics under eventful conditions.

Overview of Proposed Work

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.
- 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.

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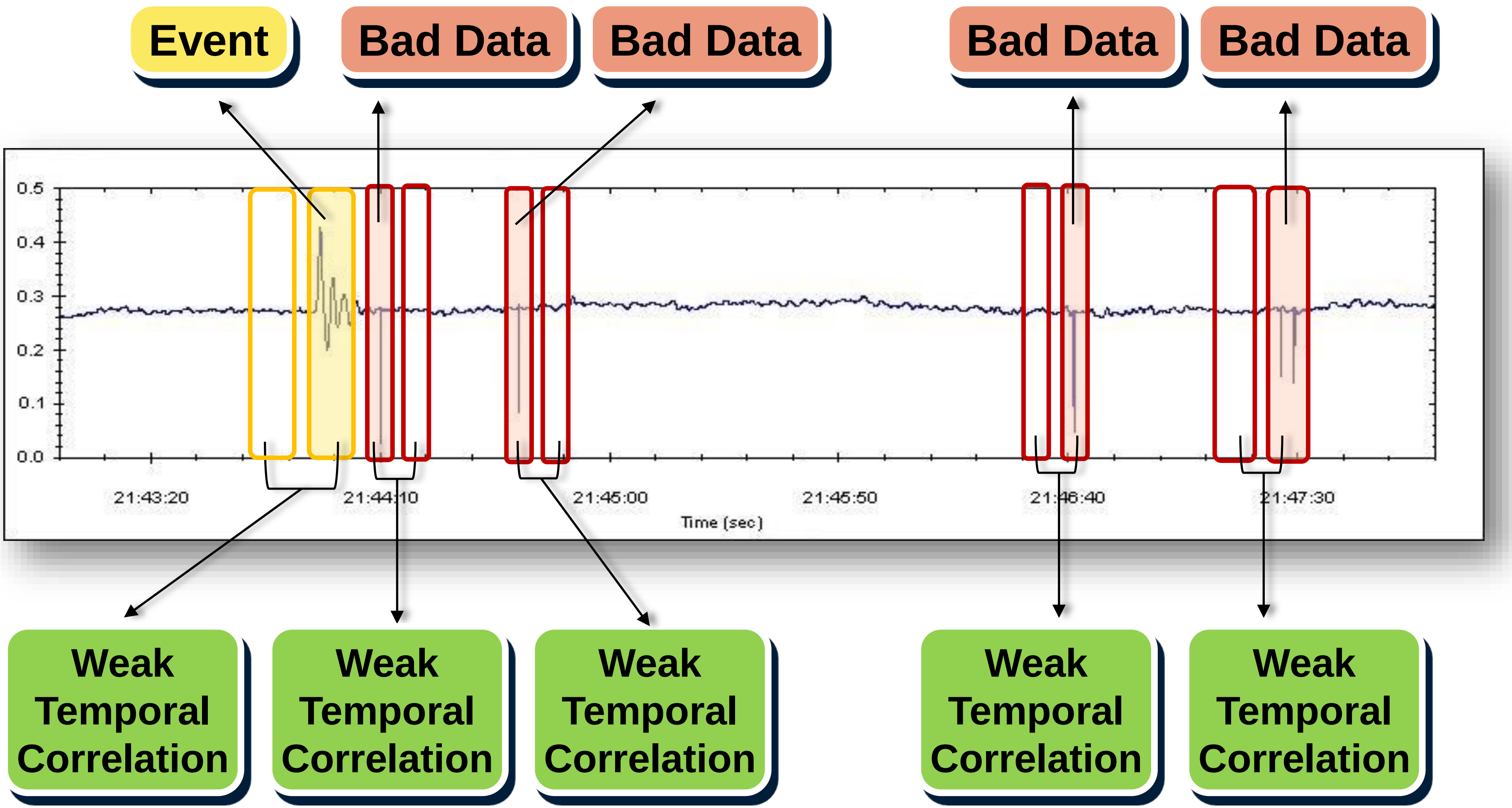
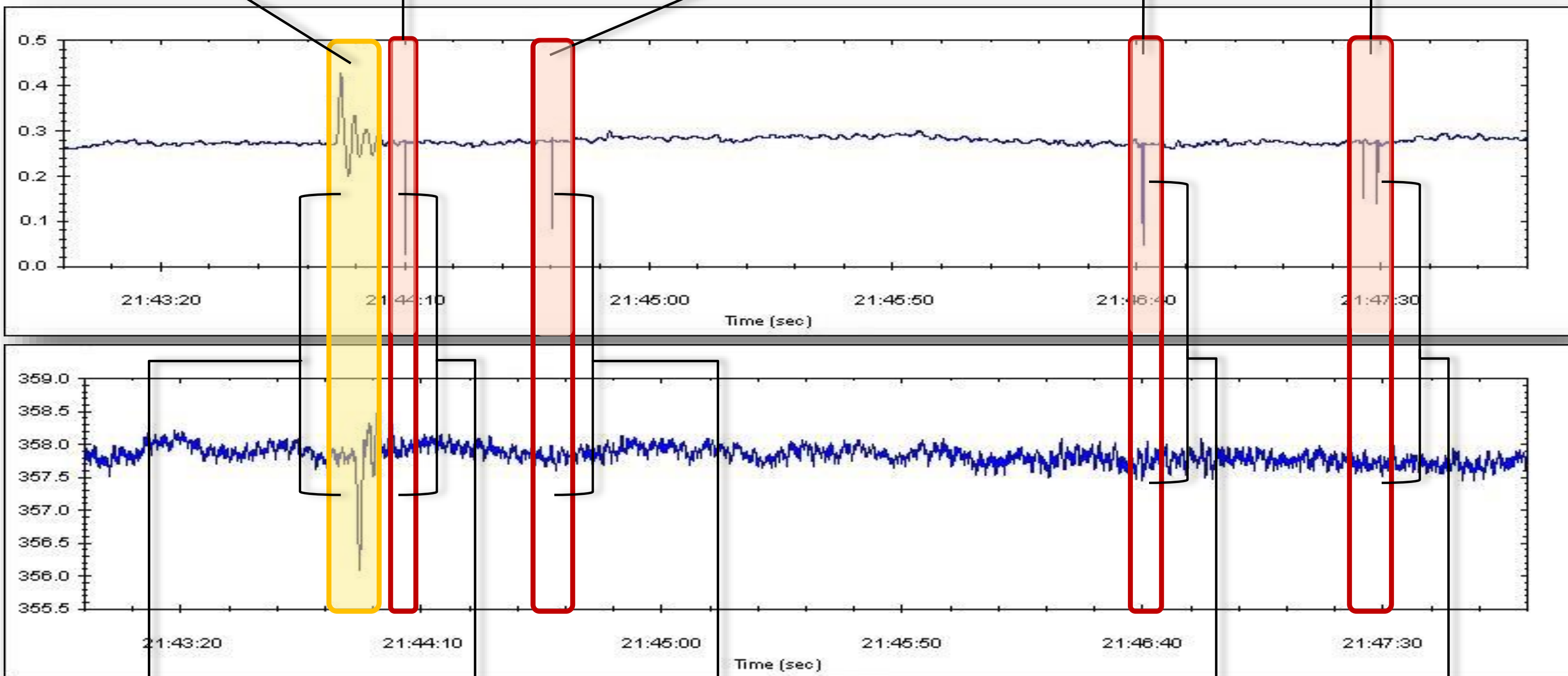
Good Data vs Eventful Data vs Bad Data

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



Good Data vs Eventful Data vs Bad Data

Event | Bad Data | Bad Data | Bad Data | Bad Data



Strong Spatial Correlation | Weak Spatial Correlation | Weak Spatial Correlation | Weak Spatial Correlation | Weak Spatial Correlation

Features of Good / Eventful / Bad Data

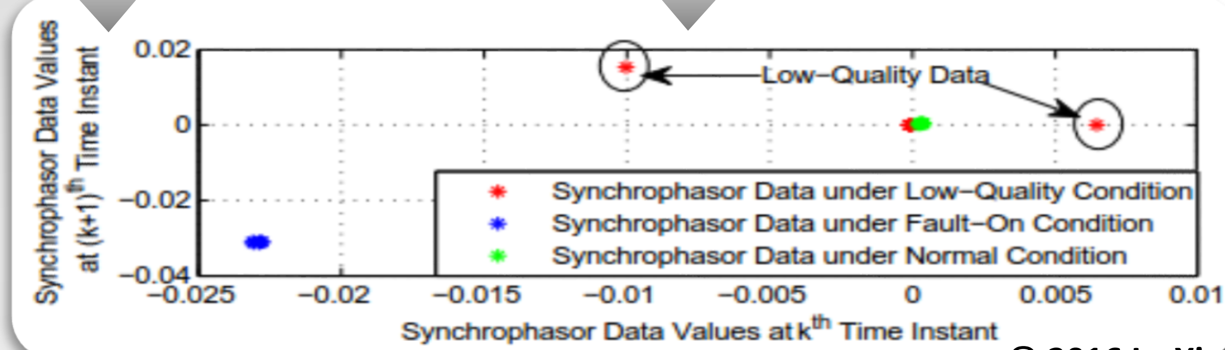
Criteria: Normal Data VS Bad / Eventful Data

- For a particular PMU curve, its bad data segment and eventful data segment have ***weak*** ***temporal*** **correlation** with its normal data segment.

Criteria: Bad Data VS Eventful Data

- For a particular PMU curve, its bad data segment has **weak *spatial* correlation** with corresponding data segments of its neighboring PMU curves.
- Its eventful data segment has **strong *spatial* correlation** with corresponding data segments of its neighboring PMU curves.

PMU Bad Data: Spatio-Temporal Outlier



Online Detection of Bad PMU Data

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.**

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:**

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

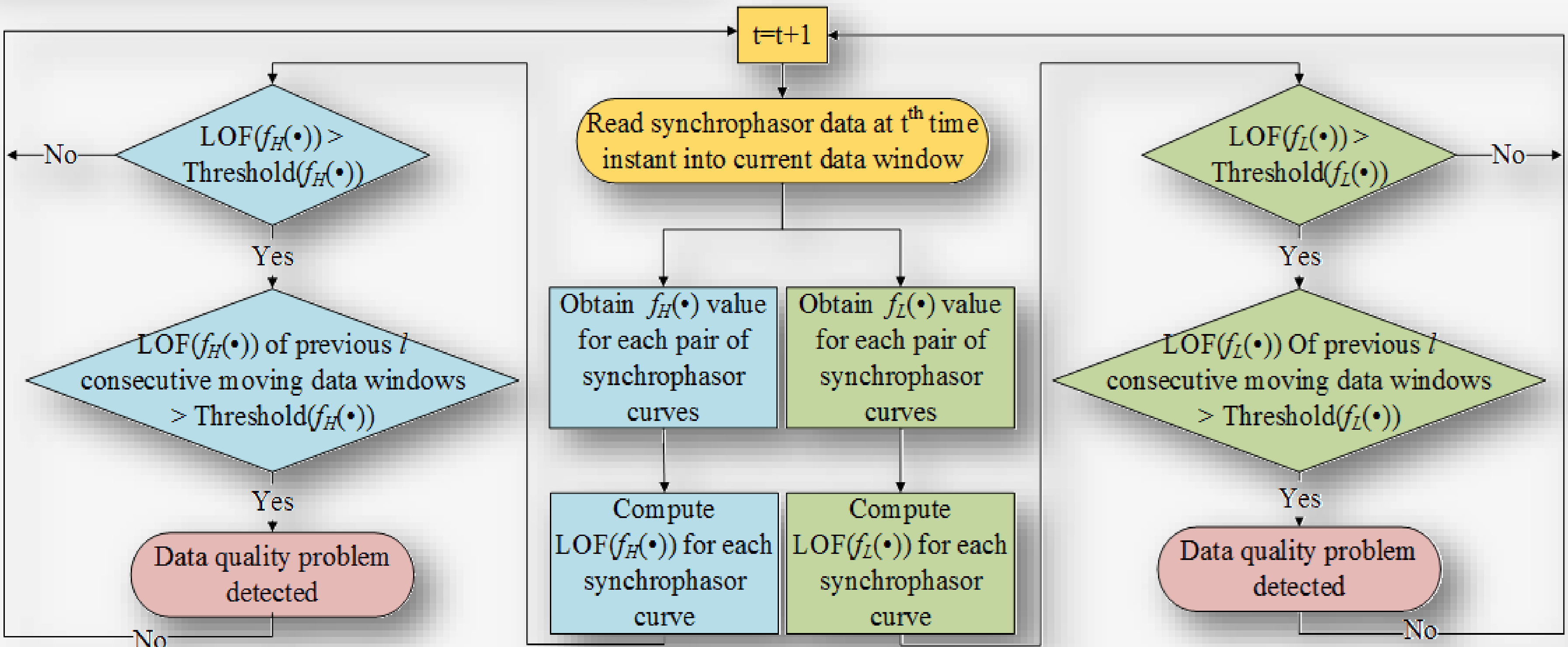
- **Bad Data Detection:**

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

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

Online Detection of Bad PMU Data

Implementation Flowchart



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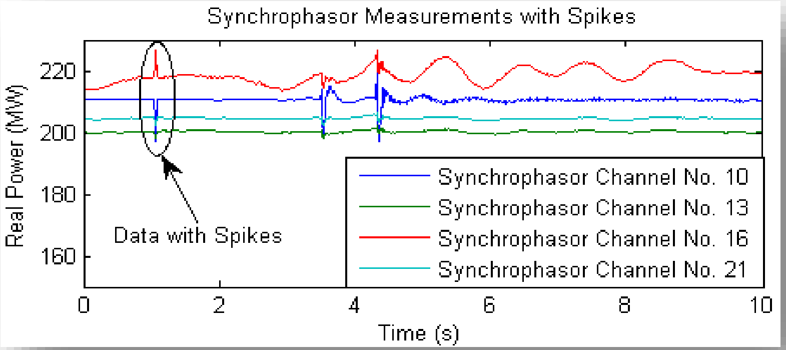
Numerical Results – Data Spikes

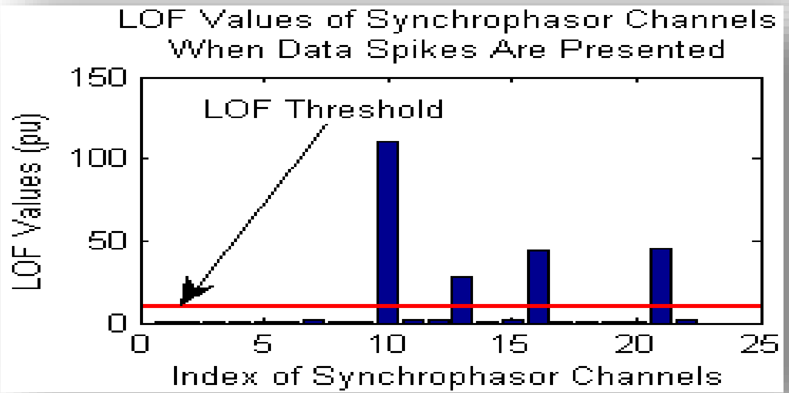
Test Case Description

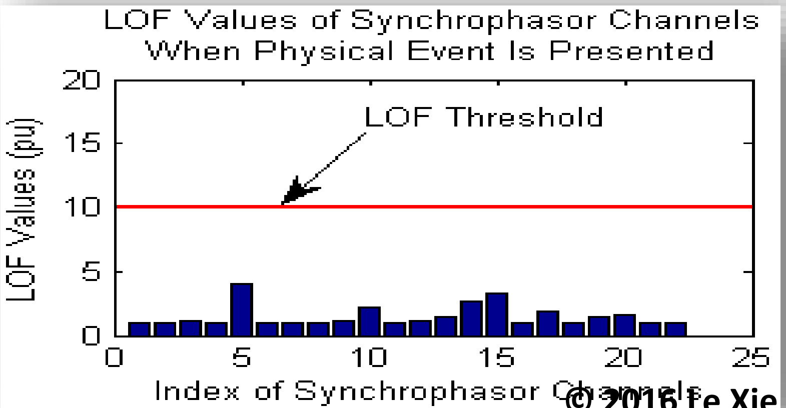
- **22 real-world PMU real power data curves.**
- **PMU No. 10, 13, 16, 21 contain data spikes lasting from 1.05s to 1.1s.**
- **Line tripping fault is presented around 4s.**

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.**







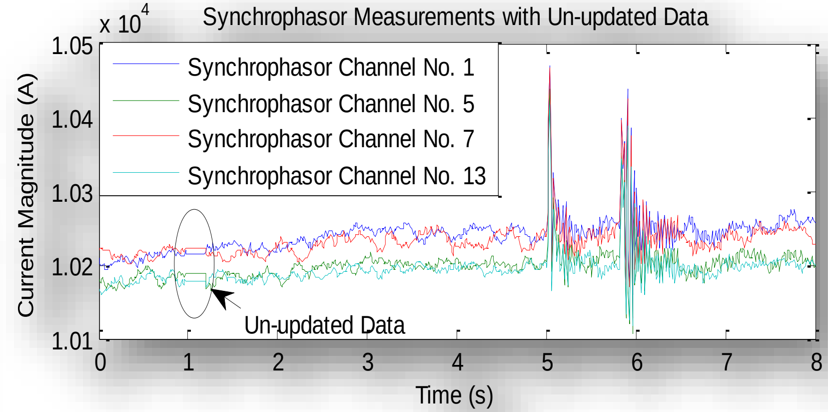
Numerical Results – Un-updated Data

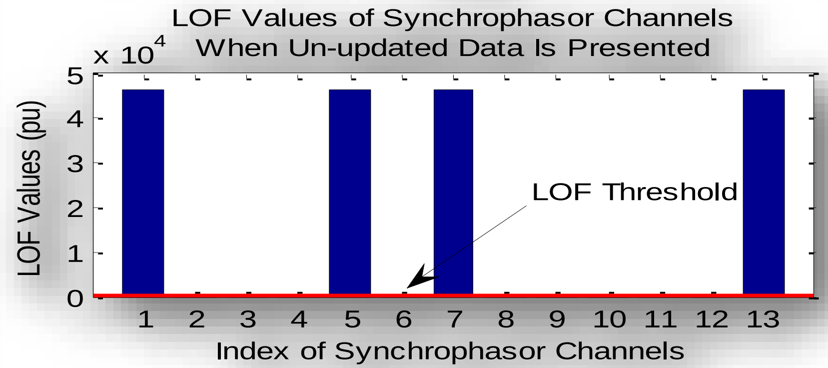
Test Case Description

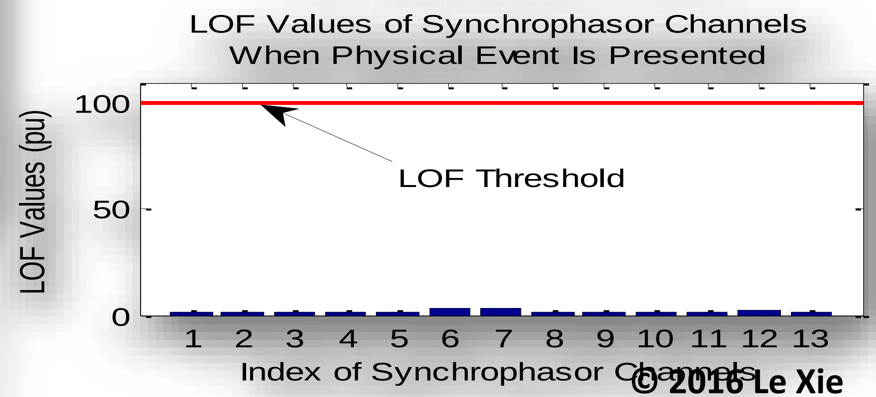
- 13 real-world PMU current magnitude data curves.
- PMU No. 1, 5, 7, 13 contain un-updated data lasting from 1s to 1.2s.
- Line tripping fault is presented around 4s.

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.







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1 Introduction

2 Technical Approach

3 Numerical Results

4 **Conclusions**

Conclusions

Conclusions

An approach for PMU bad data detection is proposed:

- **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 bad data in PMU outputs under both normal and eventful operating conditions.**

References

References

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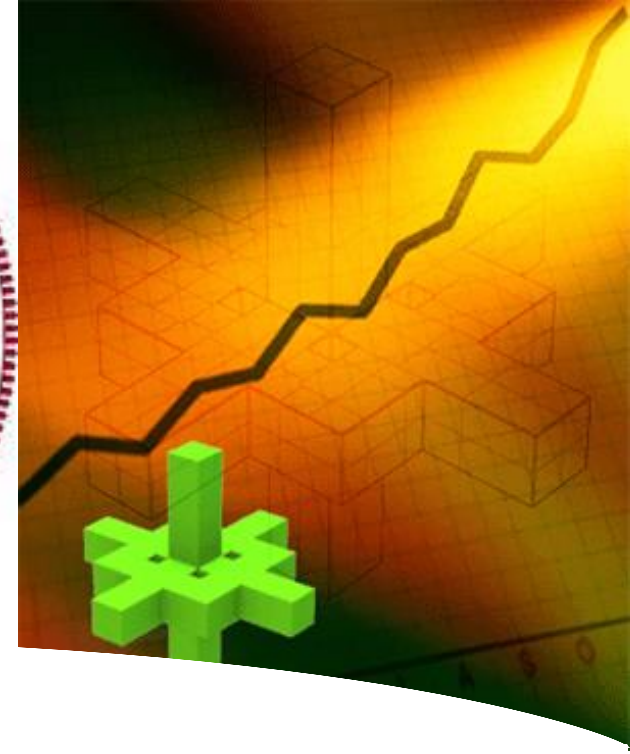
- [6] M. Wu and L. Xie, “Online identification of bad synchrophasor measurements via spatio-temporal correlations,” *19th Power Systems Computation Conference*, Genoa, Italy, 2016, accepted.

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