Dimensionality Reduction and Possible Applications with Synchrophasor Data

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Joint Work with Y. Chen, M. Wu, B. Wiseman, and Prof. P. R. Kumar

Outline

- Spatio-Temporal Correlation of Synchrophasor Data
- Dimensionality Reduction for
  - Anomaly Detection
  - Data Quality Monitoring
- Online Identification using Real-time Dynamic Data
  - Selective Modal Analysis

Growth of Synchrophasors (Real-time Big Data)

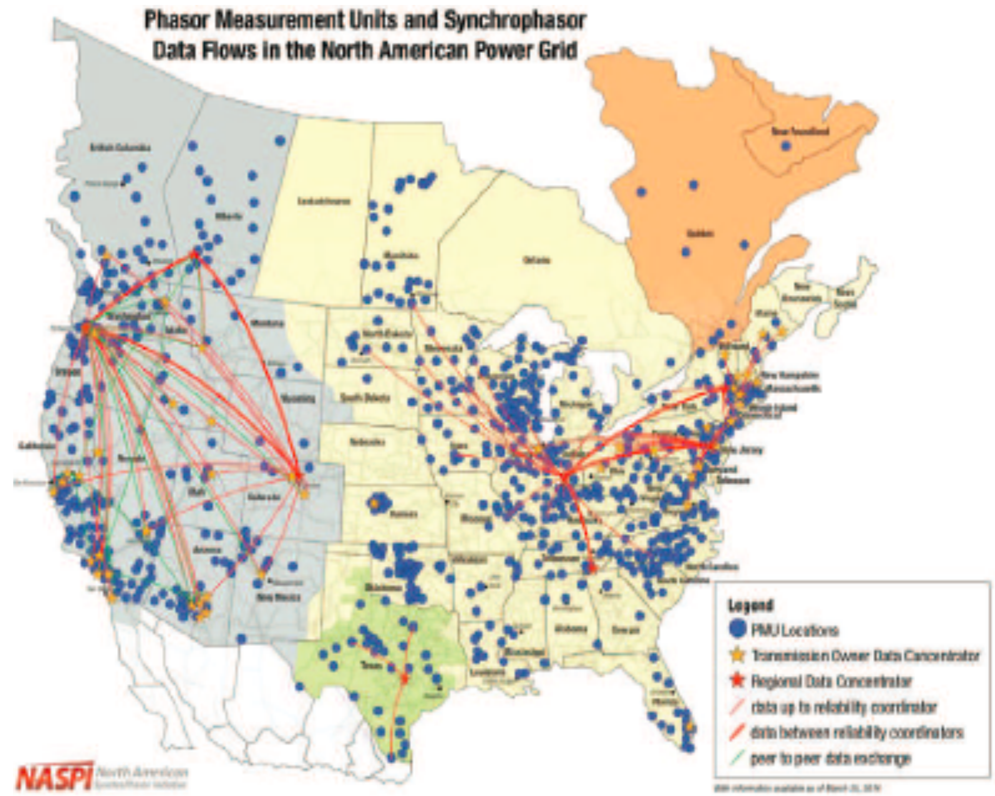
North America

Reported by NASPI*

- By March 2012, 500 networked PMUs installed.
- >1700 PMUs installed by 2015.

China

- More than 2000 PMU [Beijing Sifang, 2013].



PMU map in North America as of Oct. 2014.

*NASPI: North American SynchroPhasor Initiative.

- http://www.eia.gov/todayinenergy/detail.cfm?id=5630
- Beijing Sifang Company, “Power grid dynamic monitoring and disturbance identification,” in North American SynchroPhasor Initiative WorkGroup Meeting, Feb. 2013, 2013.

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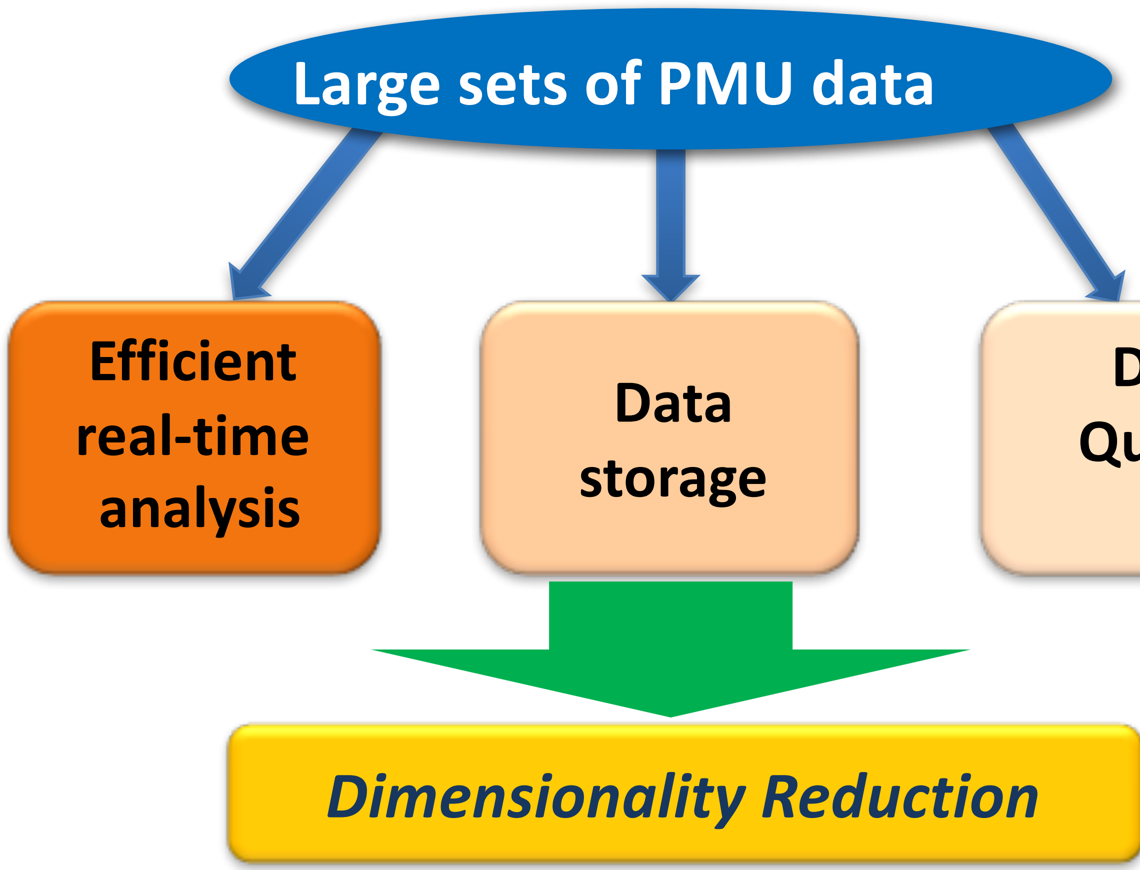
Barriers for Real-time Application

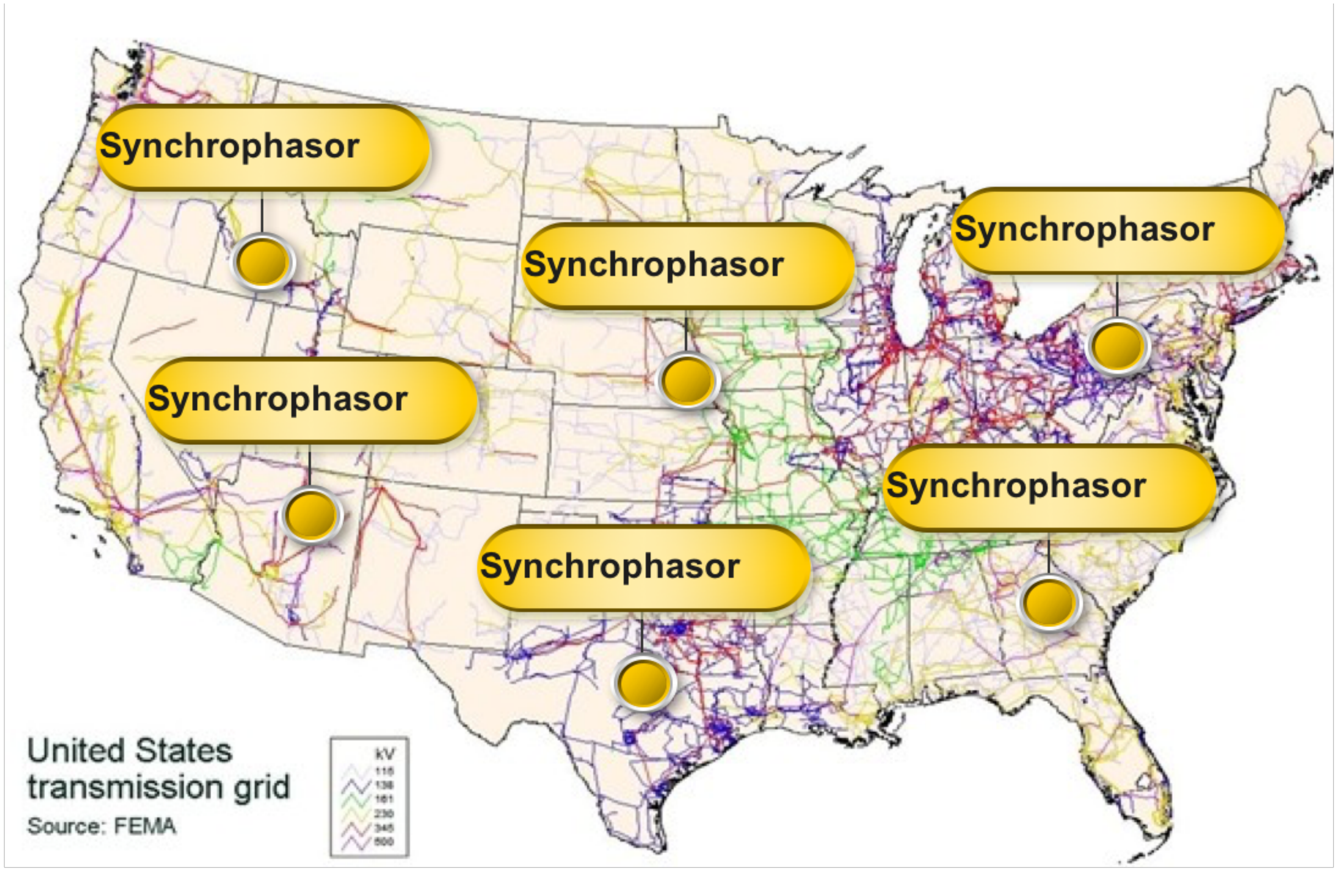


Related Work:

[5] M. Wang, J.H. Chow, P. Gao, X.T. Jiang, Y. Xia, S.G. Ghiocel, B. Fardanesh, G. Stefopolous, Y. Kokai, N. Saito, M. Razanousky, "A Low-Rank Matrix Approach for the Analysis of Large Amounts of Power System Synchrophasor Data," in System Sciences (HICSS), 2015.

[6] N. Dahal, R. King, and V. Madani, IEEE, "Online dimension reduction of synchrophasor data," in Proc. IEEE PES Transmission and Distribution Conf. Expo. (T&D), 2012.

Spatio-temporal Correlations



Early Anomaly Detection & Data Quality Monitoring (milliseconds to seconds)

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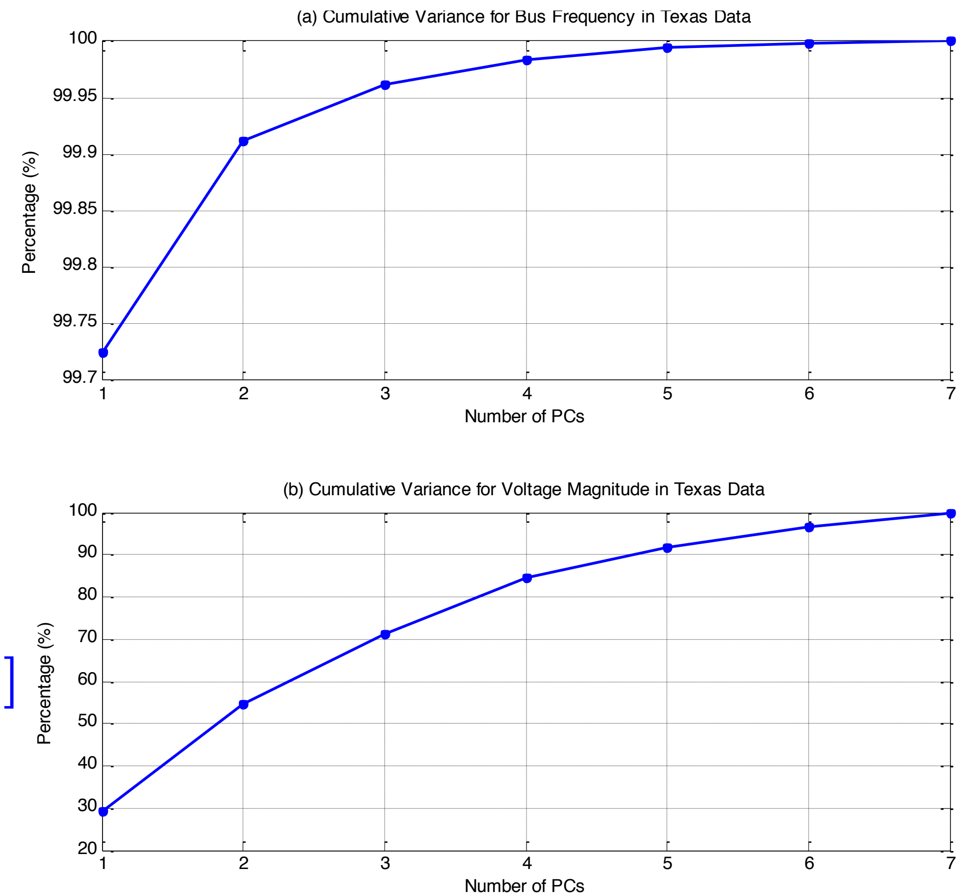
PCA for ERCOT Data

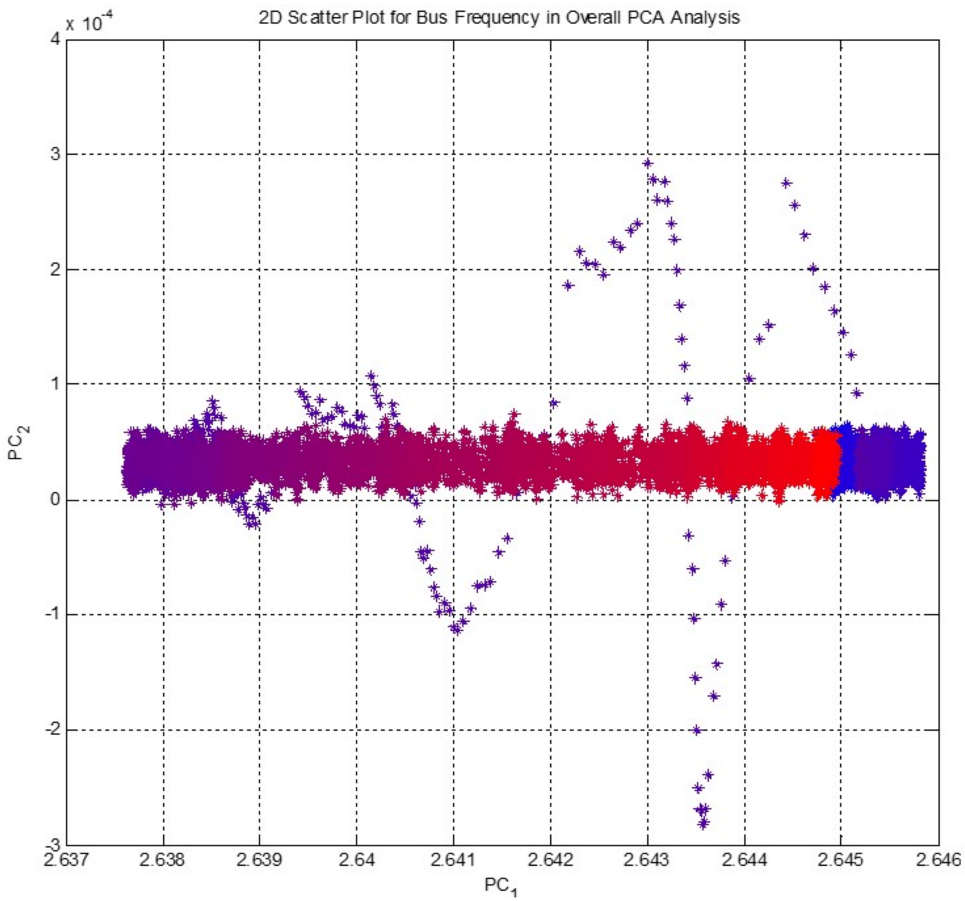
$$Y_B = [\ _5,\ \ _3]$$

$$Y_B^V = [V_2,\ V_1,\ V_7]$$

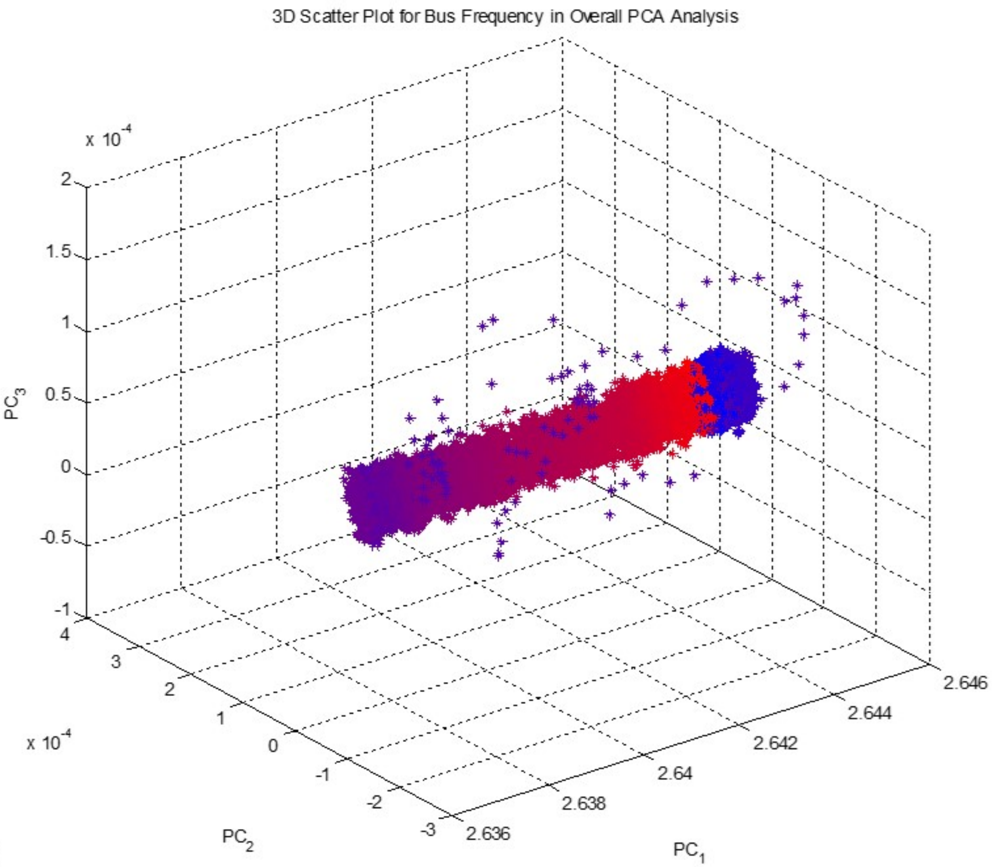


Cumulative variance for bus frequency and voltage magnitude for ERCOT data.

Scatter Plot for Frequency Data



2D Scatter plot for bus frequency.



3D Scatter plot for bus frequency.

Normal Condition

Abnormal Condition

Back to Normal Condition

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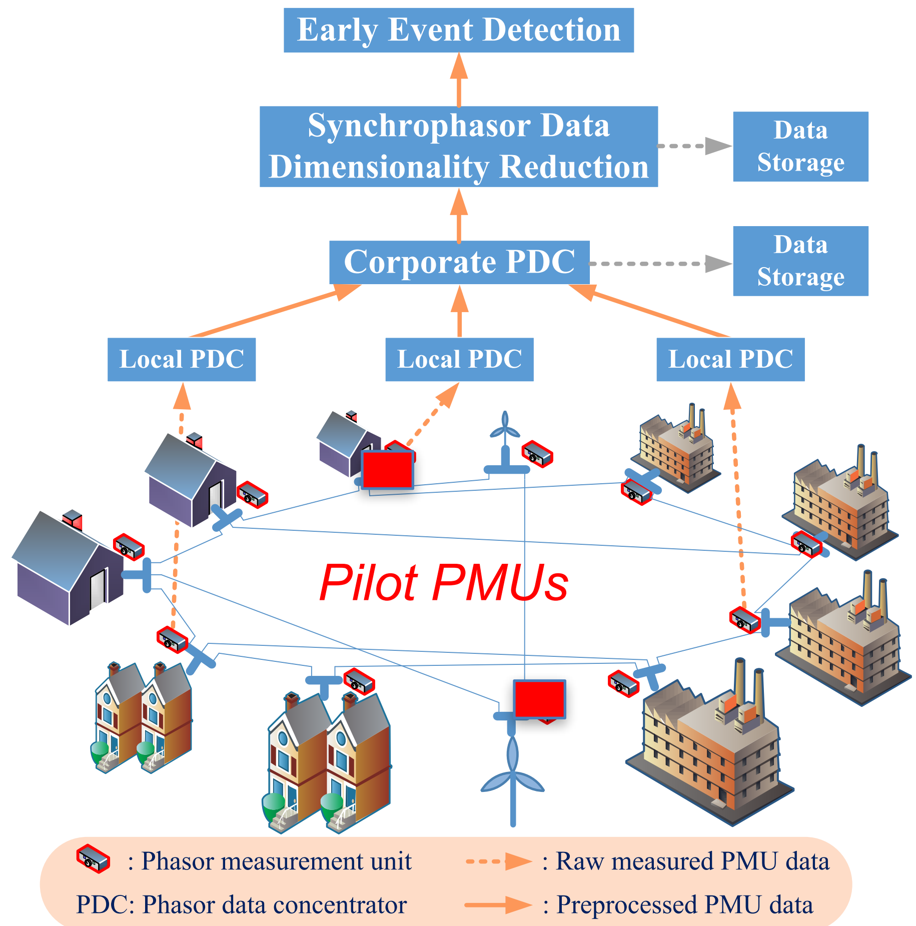
Observations

- 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 anomaly!
- But, what is the way to implement it?
- Is there any *theoretical* justification?

  Data-driven subspace change ⇔ Indication of *physical events or quality anomaly* in wide-area power systems

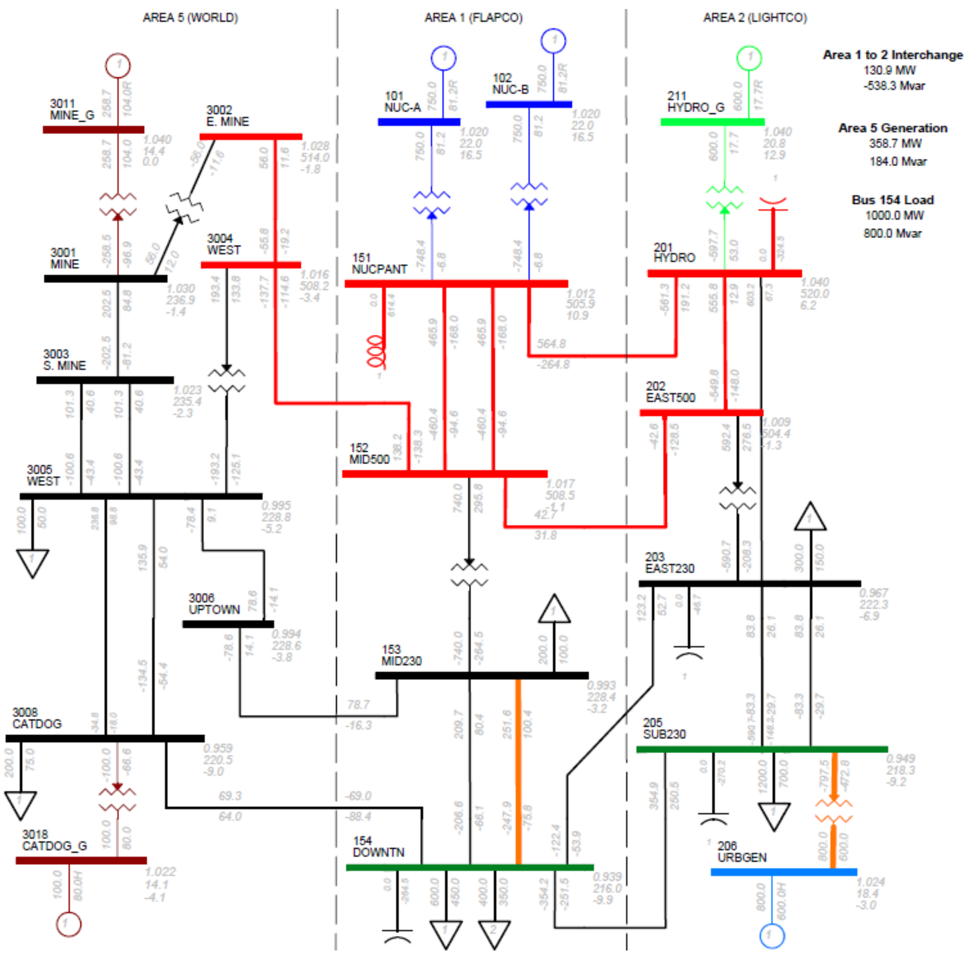
Novel Early Event Detection (NEED)



L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality reduction of synchrophasor data for early anomaly detection: linearized analysis," *IEEE Tran. Power Systems*, 2014.

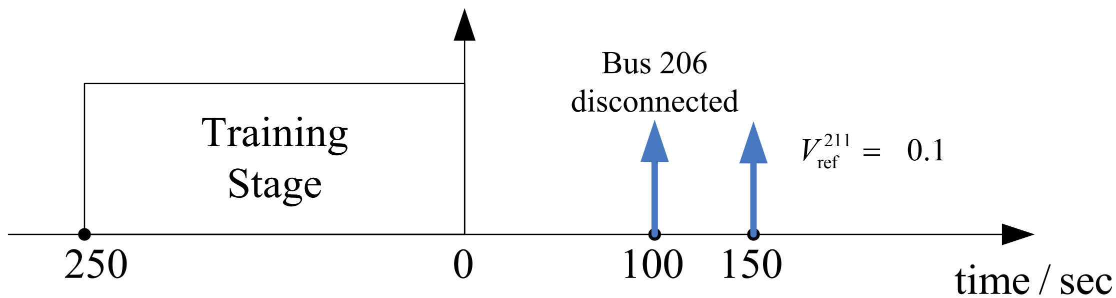
Case Study 1

- 23-bus system
- 23 PMUs.
- Measurements from 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)

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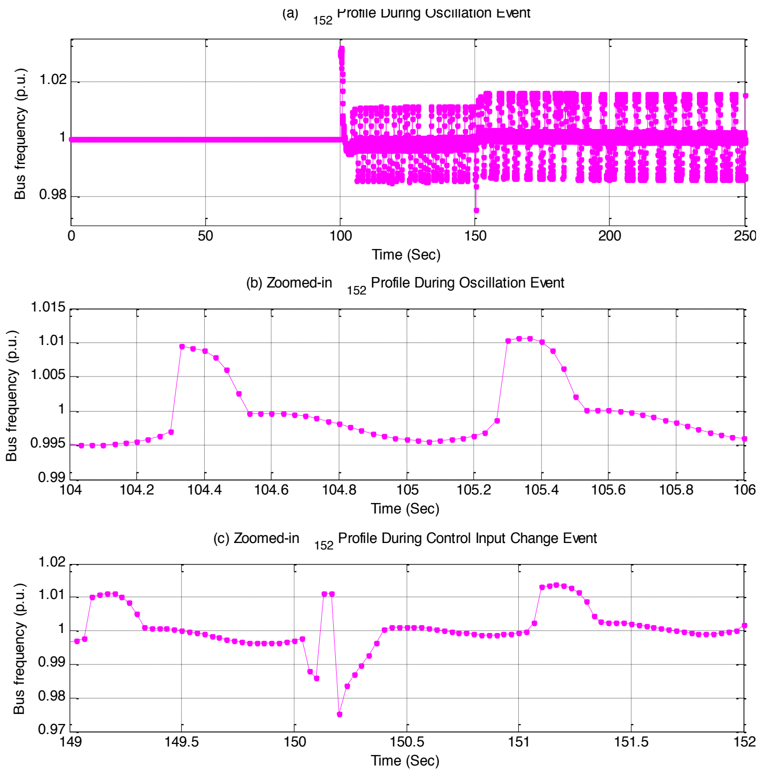
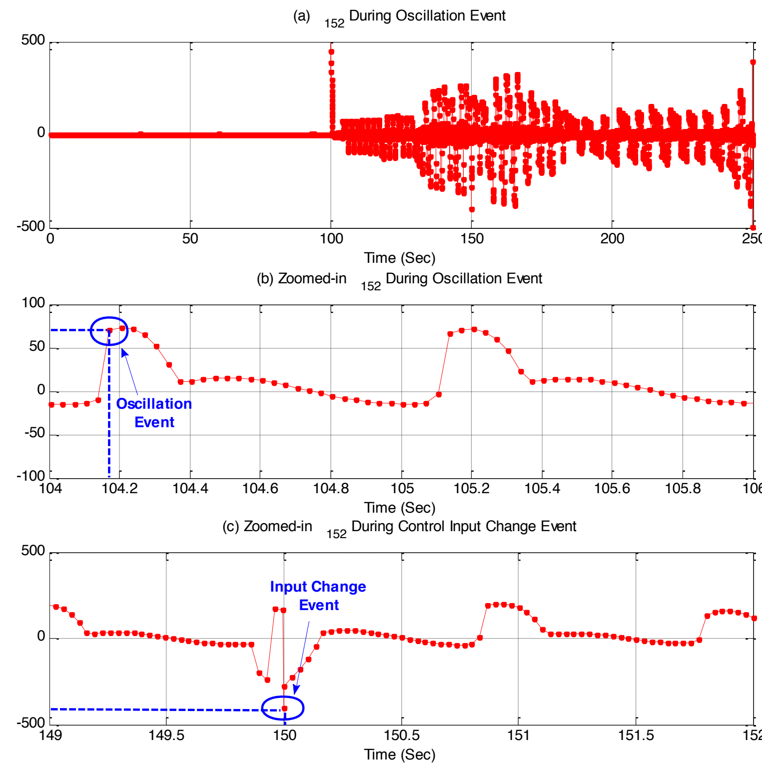
Early Event Detection



w152 **profile.**



152 **during line tripping event.**

Need for Online Data Quality Monitoring

Current Practice

- Utilities and vendors are developing more and more synchrophasor-based decision making tools.
- Synchrophasor data has much higher sampling rate and accuracy requirement compared with traditional SCADA data.
- Typical bad data ratio of synchrophasors in California ISO ranges from 10% to 17% (in 2011) [6].

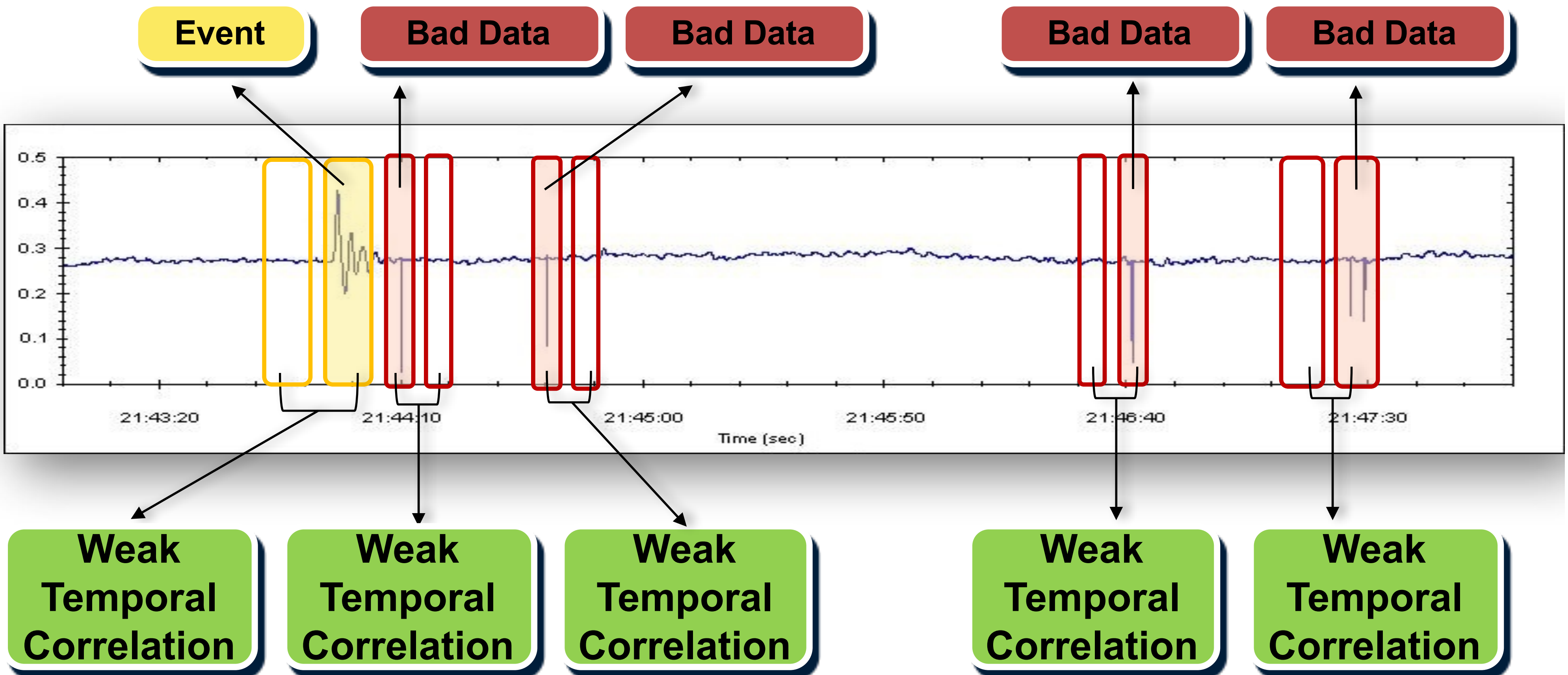
Critical Needs

- There is an urgent need to develop scalable, real-time methods to monitor and improve synchrophasor data quality.
- Conventional bad data detection algorithms are rendered ineffective, novel algorithms are needed.

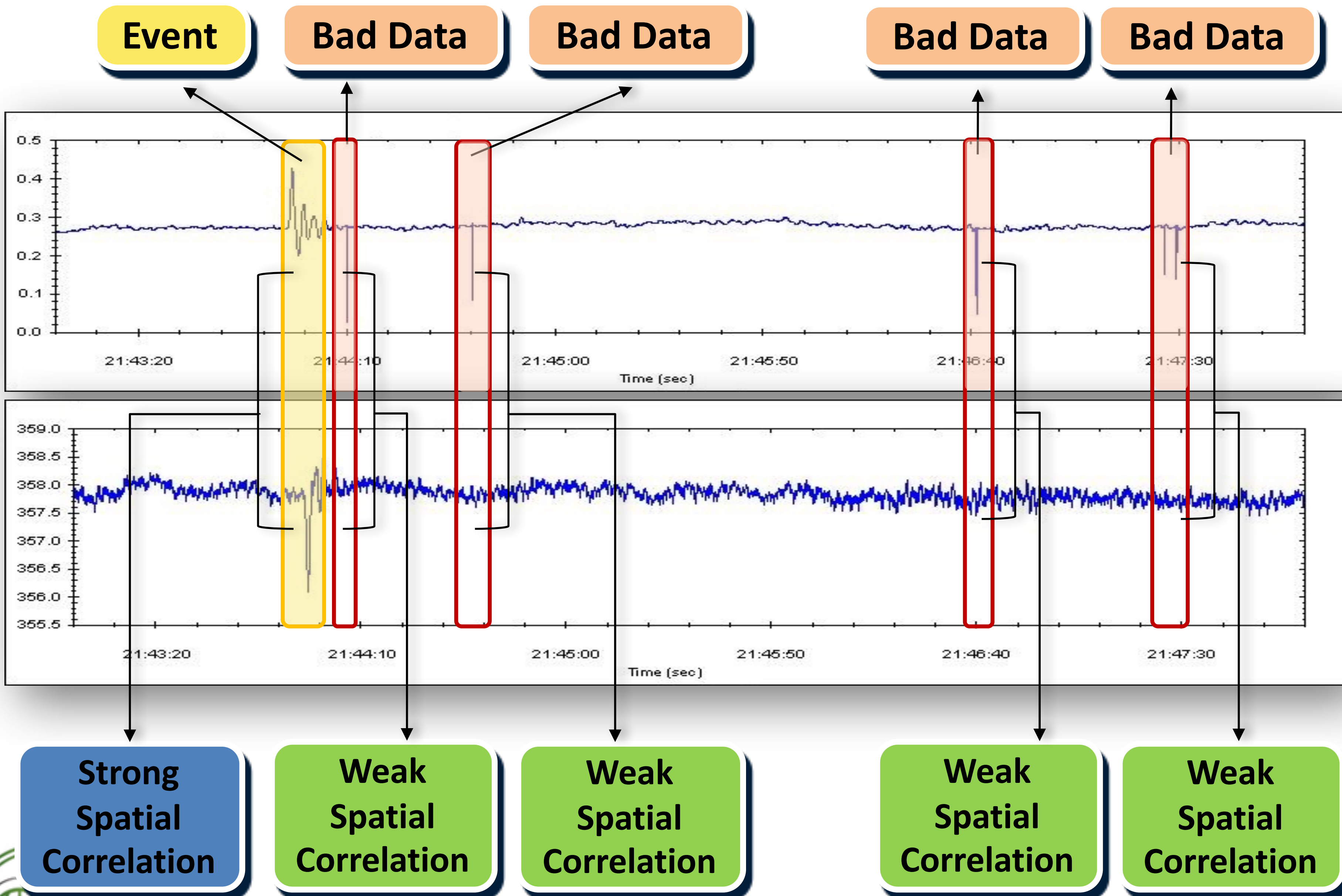
- M. Wu and L. Xie, "Online identification of bad synchrophasor measurements via spatio-temporal correlations," *19th Power Systems Computation Conference*, Genoa, Italy, 2016.

Physical Events or Bad Data?

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



Good Data vs Eventful Data vs Bad Data



Features of Good / Eventful / Bad Data

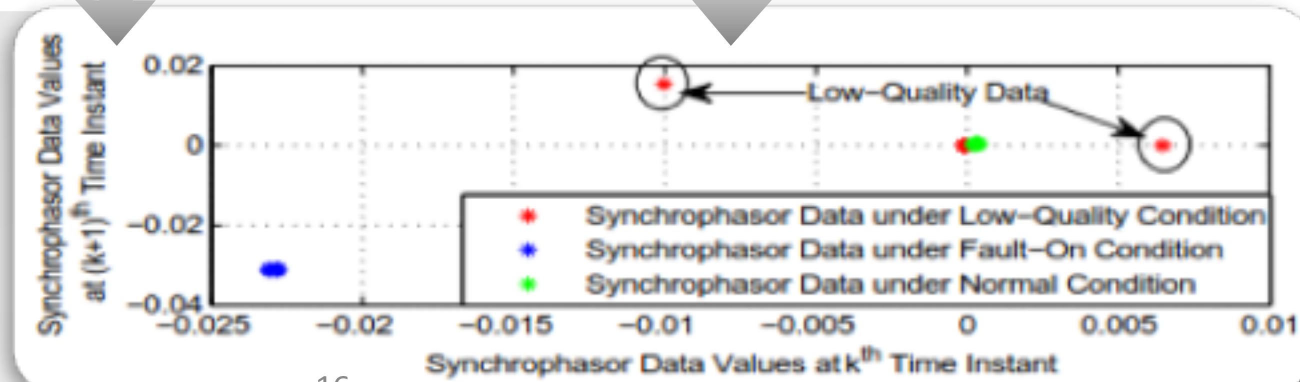
Criteria: Normal Data VS Bad / Eventful Data

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

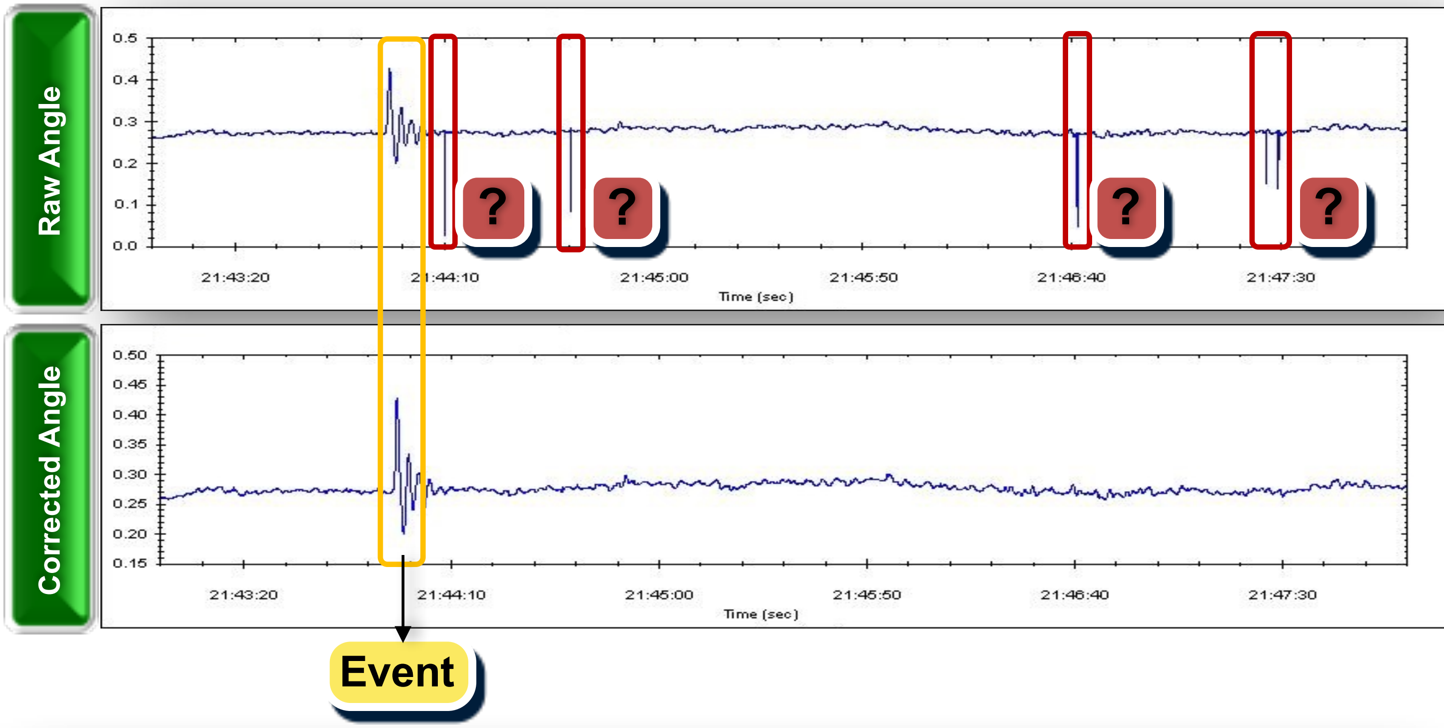
Criteria: Bad Data VS Eventful Data

- 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



Voltage Phase Angle after Data Correction



- **Spikes fixed using a smoothing filter**
- **Corrected angle - excellent signal for analysis.**

Dynamic Data for Dynamic Systems

- Can we use PMU data to develop simple models describing key system characteristics in real time?
- Could we develop frequency-targeted system identification to recover key system modes?

B. Wiseman, Y. Chen, P. R. Kumar and L. Xie, "PMU-based Reduced-order Modeling of Power System Dynamics via Selective Modal Analysis," *IEEE T&D 2016.*

Data-driven Selective Modal Analysis

TABLE II
RESULTS OF TARGETED MODE SELECTION

Selected Eigenvalues	Damping Ratio	Frequency (Hz)
$\lambda_{1,2} = -0.0917 \pm j7.6626$	0.012	1.22
$\lambda_{3,4} = -0.3607 \pm j5.1037$	0.071	0.81
$\lambda_{5,6} = -0.1399 \pm j2.0713$	0.067	0.33

TABLE III
RELEVANT STATES IDENTIFICATION THROUGH PARTICIPATION FACTORS

Eigenvalues	Relevant States	Individual NPF	Total NPF
$\lambda_{1,2}$	δ_1, ω_1	2×0.4922	0.9844
$\lambda_{3,4}$	δ_3, ω_3 δ_4, ω_4	2×0.2456 2×0.2088	0.9088
$\lambda_{5,6}$	δ_4, ω_4 δ_3, ω_3	2×0.1287 2×0.1562	0.6298

TABLE IV
ESTIMATION OF SELECTED EIGENVALUES WITH SMA

Iteration	$\lambda_{1,2}$	$\lambda_{3,4}$	$\lambda_{5,6}$
0	-0.063 $\pm$ j7.636	-0.006 $\pm$ j5.223	-0.006 $\pm$ j1.762
1	-0.094 $\pm$ j7.665	-0.338 $\pm$ j5.068	-0.337 $\pm$ j2.183
2	-0.092 $\pm$ j7.662	-0.364 $\pm$ j5.100	-0.055 $\pm$ j2.040
3	**-0.092 $\pm$ j7.663**	**-0.361 $\pm$ j5.104**	-0.184 $\pm$ j2.062
4	-0.092 $\pm$ j7.663	-0.361 $\pm$ j5.104	-0.123 $\pm$ j2.082
5	-0.092 $\pm$ j7.663	-0.361 $\pm$ j5.104	-0.145 $\pm$ j2.063
6	-0.092 $\pm$ j7.663	-0.361 $\pm$ j5.104	-0.139 $\pm$ j2.076
7	-0.092 $\pm$ j7.663	-0.361 $\pm$ j5.104	**-0.1394 $\pm$ j2.069**
True Value	*-0.0917 $\pm$ j7.6626*	*-0.3607 $\pm$ j5.1037*	*-0.1399 $\pm$ j2.0713*

TABLE VI
COMPARISON OF EIGENVALUES FROM IDENTIFIED MODEL

Eigenvalues	2^{nd}-order Model	*28^{th}-order Model*
$\lambda_{1,2}$	$-0.0920 \pm j7.6344$	*-0.0917$\pm$ j7.6626*

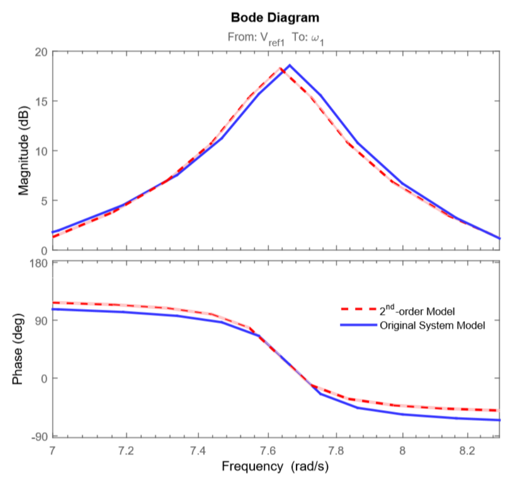


Fig. 3. Bode plot comparison of the identified and original models.

B. Wiseman, Y. Chen, P. R. Kumar and L. Xie, “PMU-based Reduced-order Modeling of Power System Dynamics via Selective Modal Analysis,” *IEEE T&D 2016.*

Summary

- Spatio-temporal correlations among synchrophasor data offer unique opportunities to develop real-time, scalable algorithms for
  - Anomaly detection
  - Data quality monitoring
  - System identification
- Much more needs to be done!
  - *Grid* model validation (in addition to components)
  - Cyber attack awareness and countermeasures.

Key References

- [1] K. Martin, “Synchrophasor data diagnostics: detection & resolution of data problems for operations and analysis”, in *Electric Power Group Webinar Series*, Jan 2014.
- [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.
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- [5] Anurag Srivastava, “Meeting PMU data quality requirements for mission critical applications”, in *PSERC Public Webinar Series*, Nov 2015.
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