Integration of Large Data Sets for Improved Decision-Making in Bulk Power Systems: Two Case Studies

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PSERC Webinar
October 20, 2015

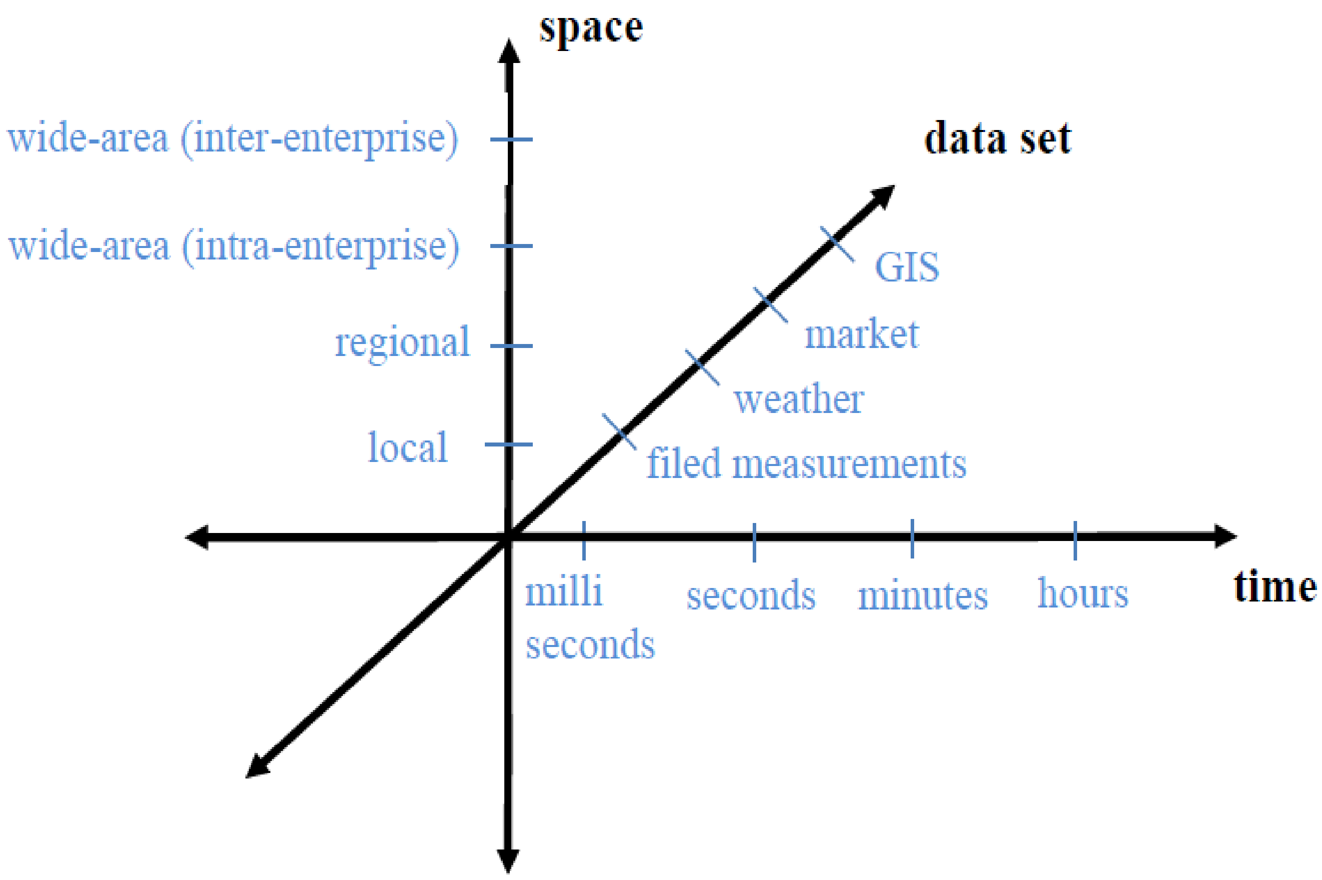
Presentation Outline

- **Brief Overview of PSERC T-51**
- ***Spatio-temporal* Correlations among Data Sets**
- **Case Study 1: Renewable Forecast**
- **Case Study 2: Synchrophasor dimensionality reduction and early anomaly detection**
- **Concluding Remarks**

T-51 Project Objectives

- Improved decision-making by utilization of large data sets – “Big Data”
- The integration of emerging large-data sets to support advanced analytics, to enhance electricity system management (planning, operations and control)
- Correlation of data in time and space and assuring consistent data semantic and syntax

Big Data in Bulk Power Systems: Opportunities and Challenges



[4] M. Kezunovic, L. Xie, and S. Grijalva, "The role of big data in improving power system operation and protection," Bulk Power System Dynamics and Control - IX Optimization, Security and Control of the Emerging Power Grid (IREP), 2013 IREP Symposium.

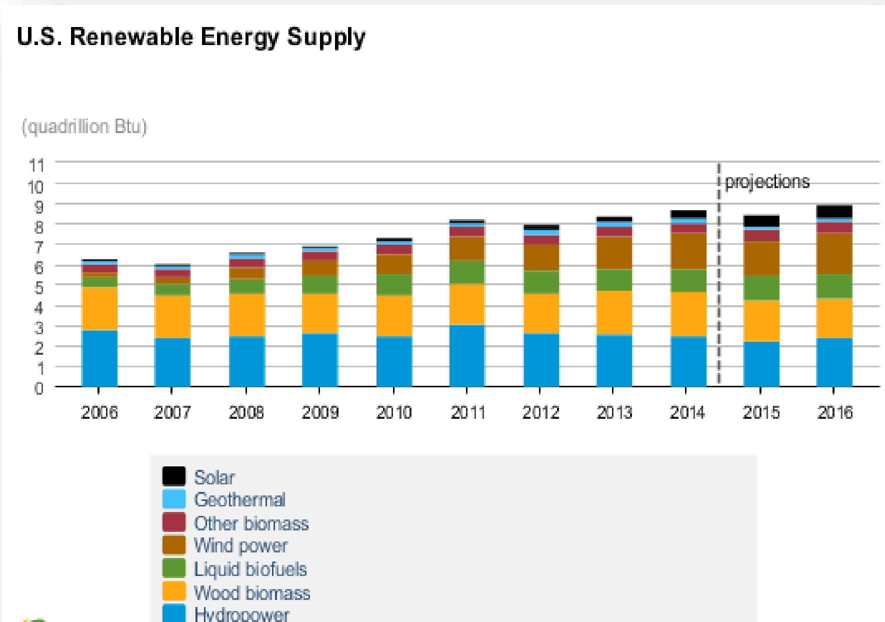
T-51 Project Summary

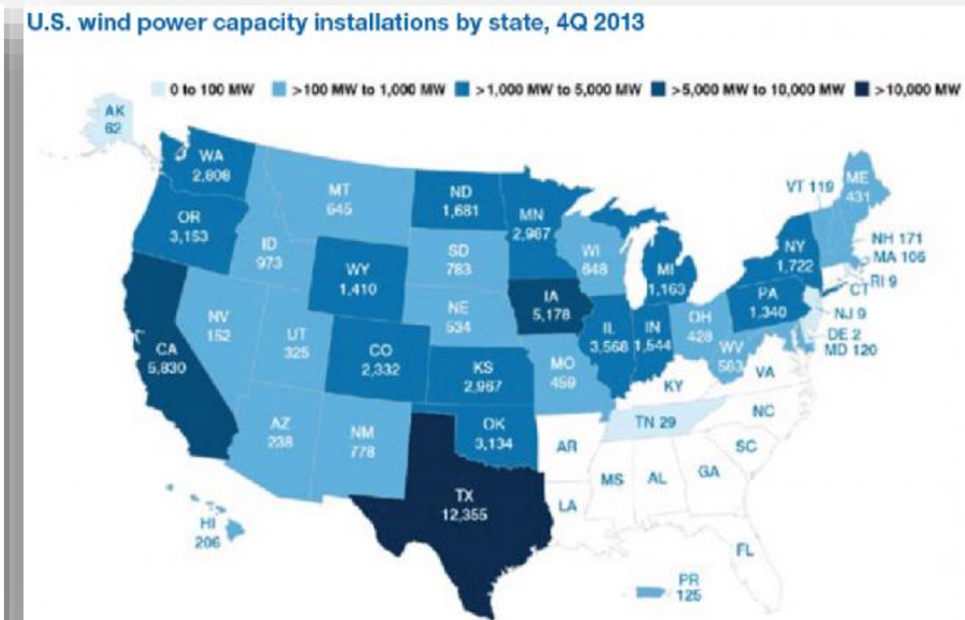
- Project duration: 2013-2015, final report available at PSERC
- Use of Big Data for Outage and Asset Management (Kezunovic, lead PI)
- Distributed Database for Future Grid (Grijalva and Chau)
- Spatio-Temporal Analytics for Renewables (Xie)
  - Wind power prediction and its economic benefits
  - Solar power prediction and quantified economic benefits

Growth of Renewable Generation (and Data)

Renewable Growth in US

- In 2014, renewable energy sources account for 16.28% of total installed U.S. operating generating capacity.
- Solar, wind, biomass, geothermal, and hydropower provided 55.7% of new installed U.S. electrical generating capacity during the first half of 2014 (1,965 MW of the 3,529 MW total installed).





http://www.renewableenergyworld.com
http://www.eia.gov/
http://www.triplepundit.com/

Growth of Synchrophasors (PMU)

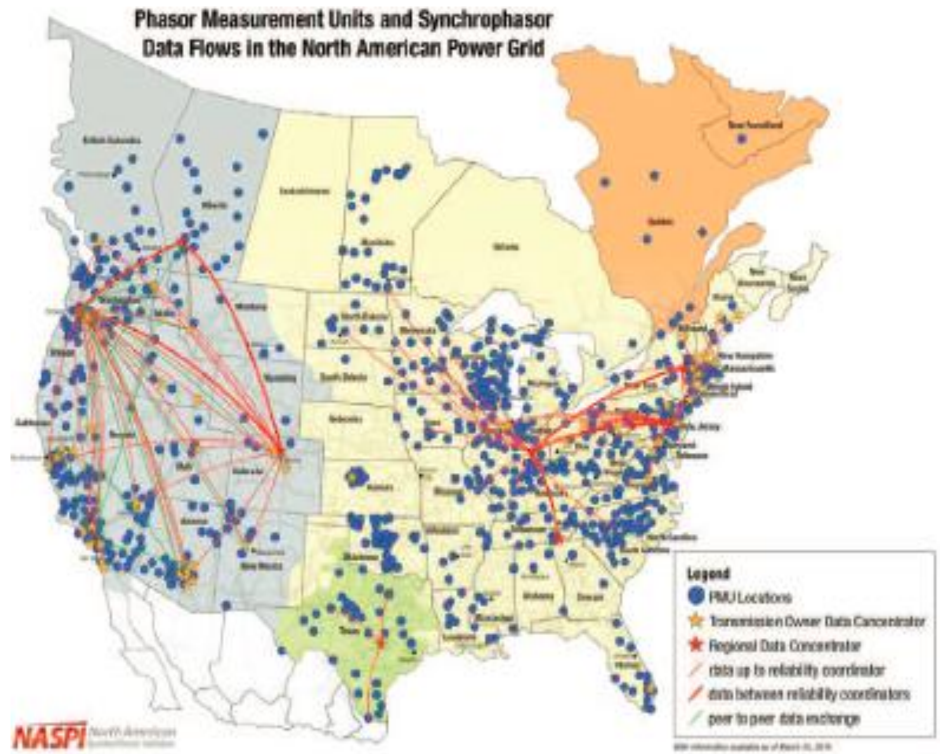
North America

Reported by NASPI*

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

China

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

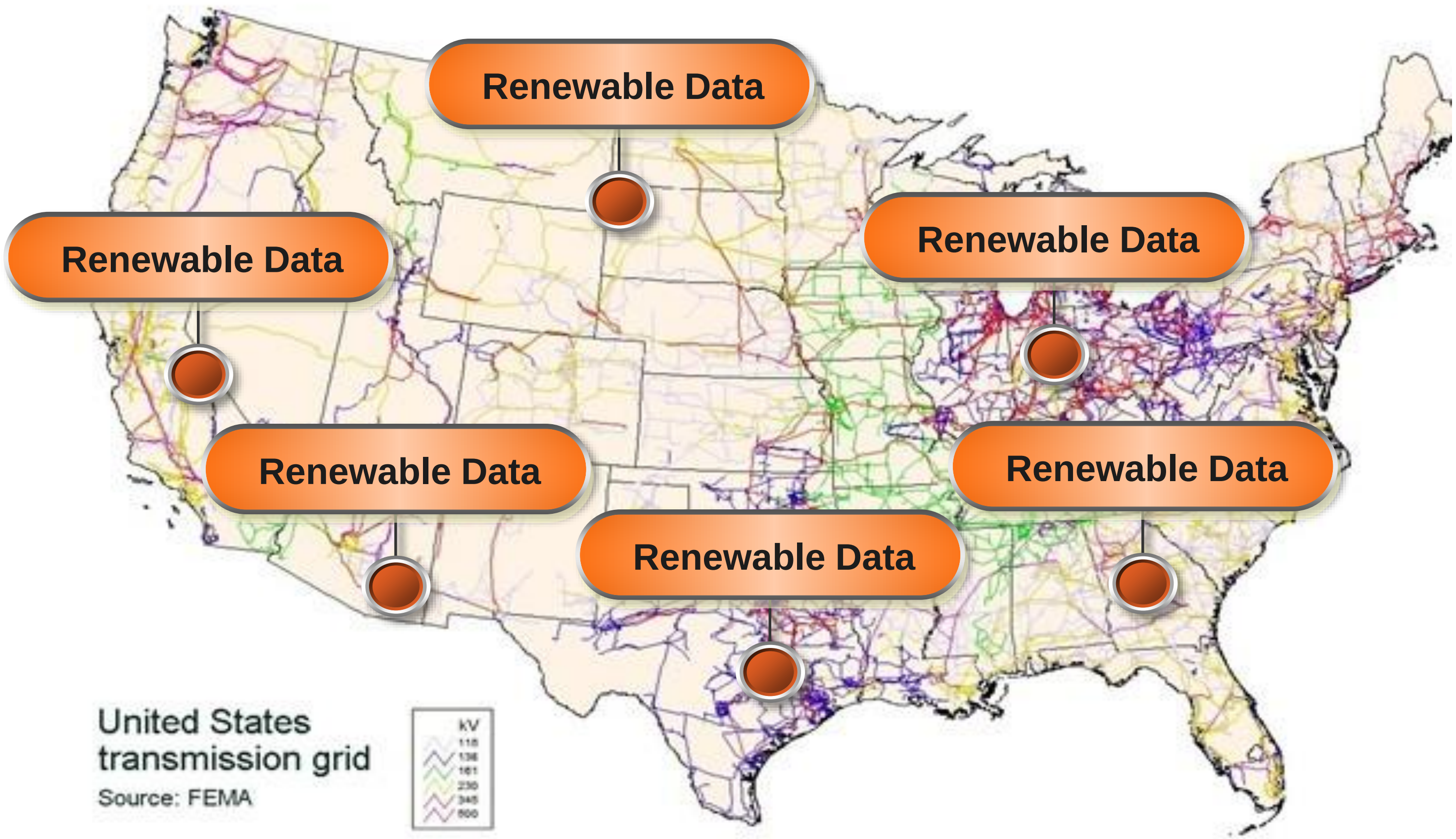


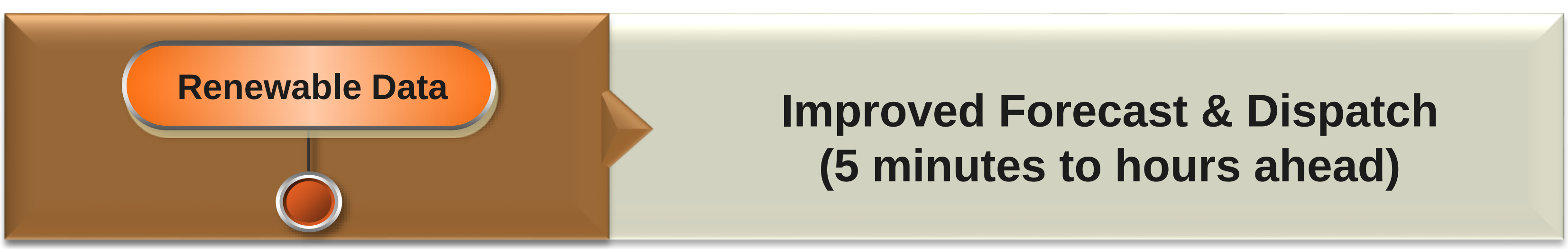
PMU map in North America as of Oct. 2014.

*NASPI: North American SynchroPhasor Initiative.

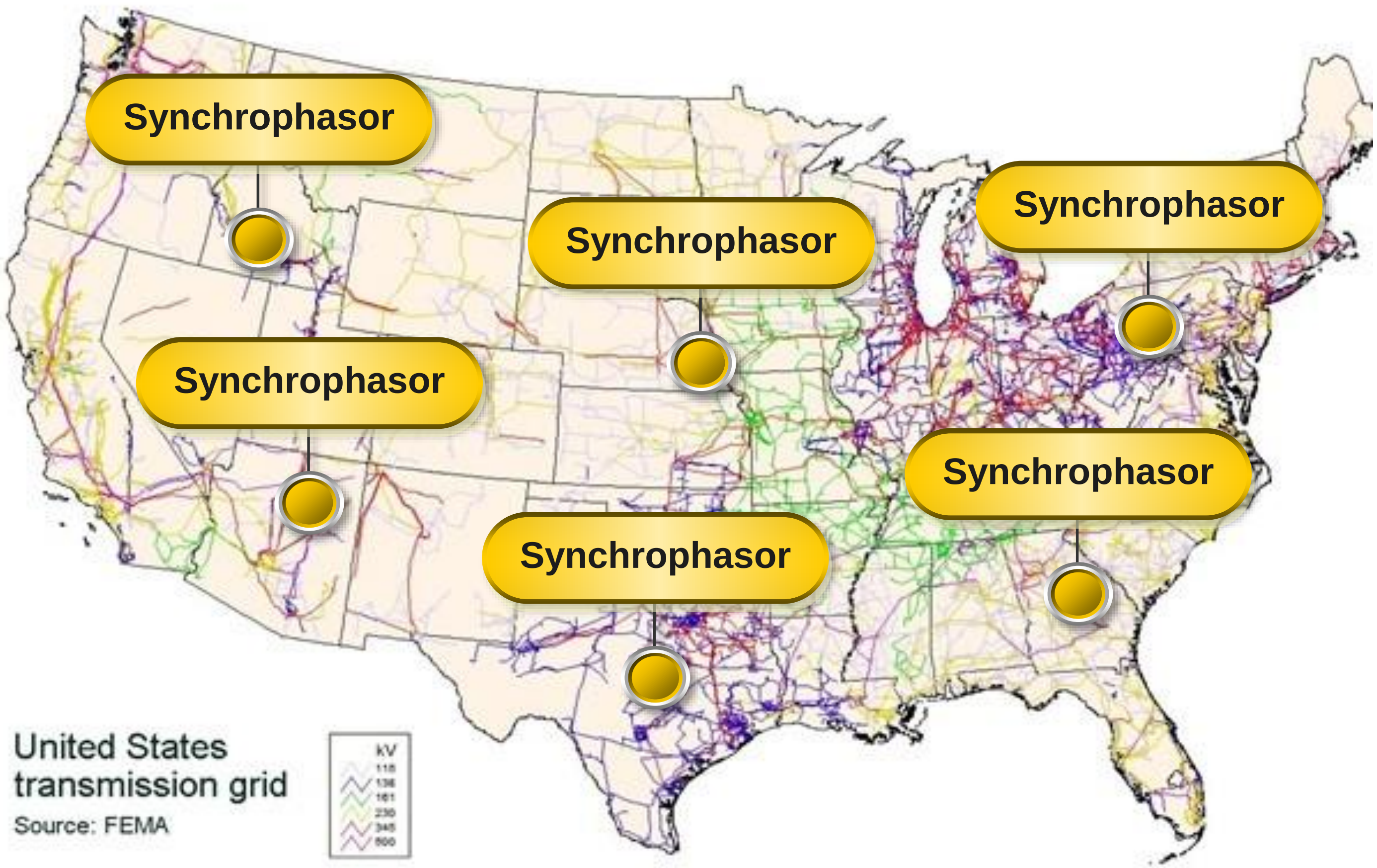
- http://www.eia.gov/todayinenergy/detail.cfm?id=5630
- Beijing Sifang Company, “Power grid dynamic monitoring and disturbance identification,” in North American SynchroPhasor Initiative WorkGroup Meeting, Feb. 2013, 2013.

Spatio-temporal Correlations at Multi Scales



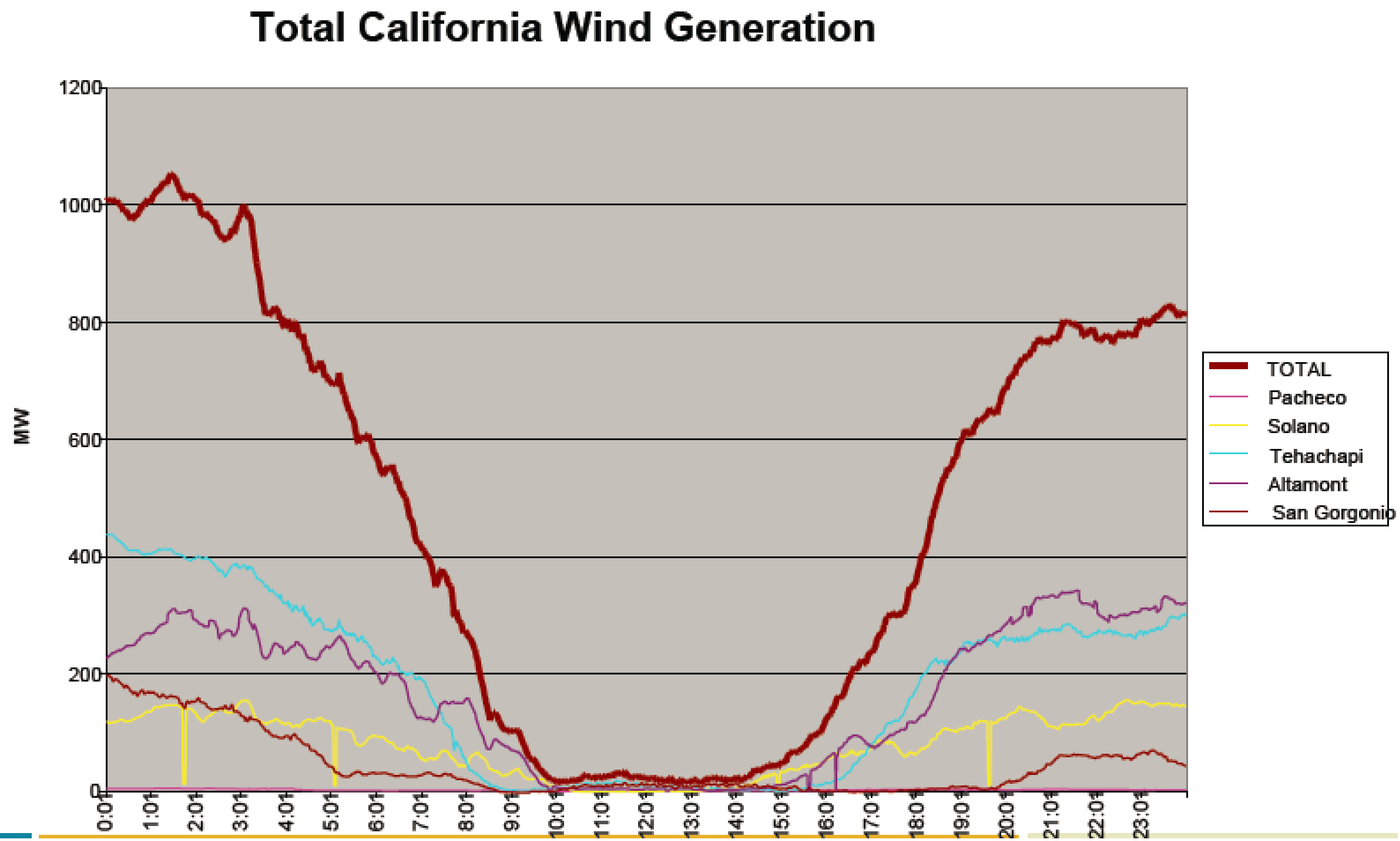


Spatio-temporal Correlations at Multi-scale



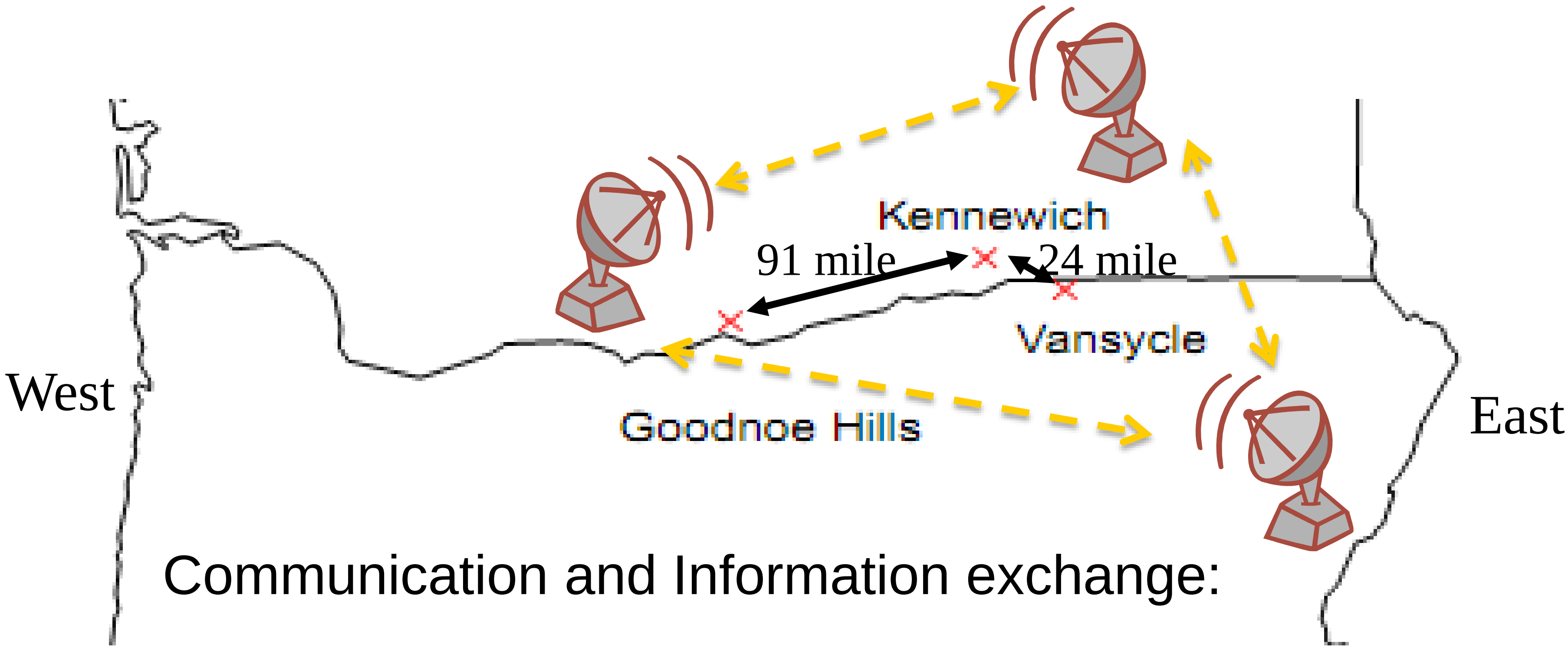
Early Anomaly Detection & Mitigation (milliseconds to seconds)

Wind Variability and Spatial Correlation



- Source: http://www.caiso.com/1c9b/1c9bd3a394f0.pdf

Spatio-Temporal Wind Forecast



Communication and Information exchange:

- Produce good wind generation forecast
- Reduce the system-wide dispatch cost
- Lower the ancillary services cost
- Incorporate more wind generation

- Related work by M. He and L. Yang and J. Zhang and V. Vittal, "A Spatio-temporal Analysis Approach for Short-term Wind Generation Forecast," IEEE Transactions on Power Systems, 2014.

Existing Methods

- Persistence (PSS) Model
  - Assume the future wind speed is the same as the current one:

$$\hat{y}_{s,t+k} = y_{s,t}$$

- Autoregressive (AR) Model:
  - Estimate $\mu^{r}_{s,t+k}$ as a linear combination of the previous wind speed at the same location

$$\mu^{r}_{s,t+k} = \alpha_0 + \sum_{i=0}^{p} \beta_i \mu^{r}_{s,t-i}$$

where $\mu^{r}_{s,t+k}$ is the residue term of center parameter of wind speed.

Spatio-Temporal Wind Speed Forecast

- The scale parameter $\sigma_{s,t+k}$ is modeled as

$$\sigma_{s,t+k} = b_0 + b_1 v_{s,t}$$

- Where b_0, b_1>0 and vs1,t is the volatility value:

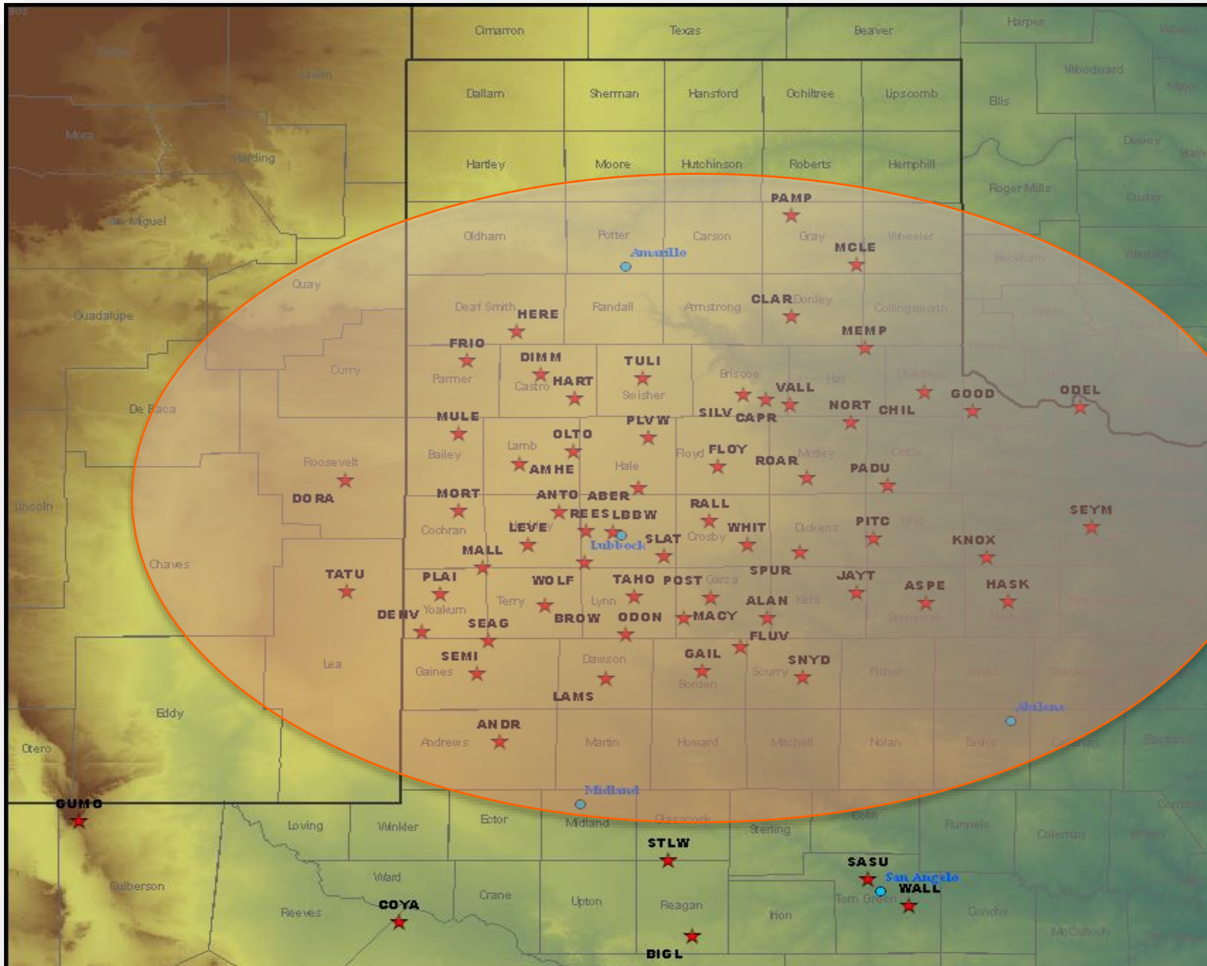
$$v_{s,t} = \sqrt{\frac{1}{2S}\sum_{s=1}^{S}\sum_{i=0}^{1}\left(\mu^r_{s,t-i} - \mu^r_{s,t-i-1}\right)^2}$$

- The residual term modeled as a linear function of current and past (up to time lag h) wind speed and trigonometric functions of wind direction.

$$\mu^r_{s,t+k} = \alpha_0 + \sum_{s=1}^{S}\sum_{j=0}^{P}\alpha_{s,j}\mu^r_{s,t-j}$$

$$+\sum_{s=1}^{S}\sum_{j=0}^{P}\beta_{s,j}\boxed{\cos\left(\theta^r_{s,t-j}\right)}+\sum_{s=1}^{S}\sum_{j=0}^{P}\gamma_{s,j}\boxed{\sin\left(\theta^r_{s,t-j}\right)}$$

Spatio-Temporal Wind Forecast
West Texas Case Study [1]



[1] L. Xie, Y. Gu, X. Zhu, and M. G. Genton, “Short-Term Spatio-Temporal Wind Power Forecast in Robust Look-ahead Power System Dispatch,” IEEE Tran. Smart Grid, 2014.

Forecast Model Performance

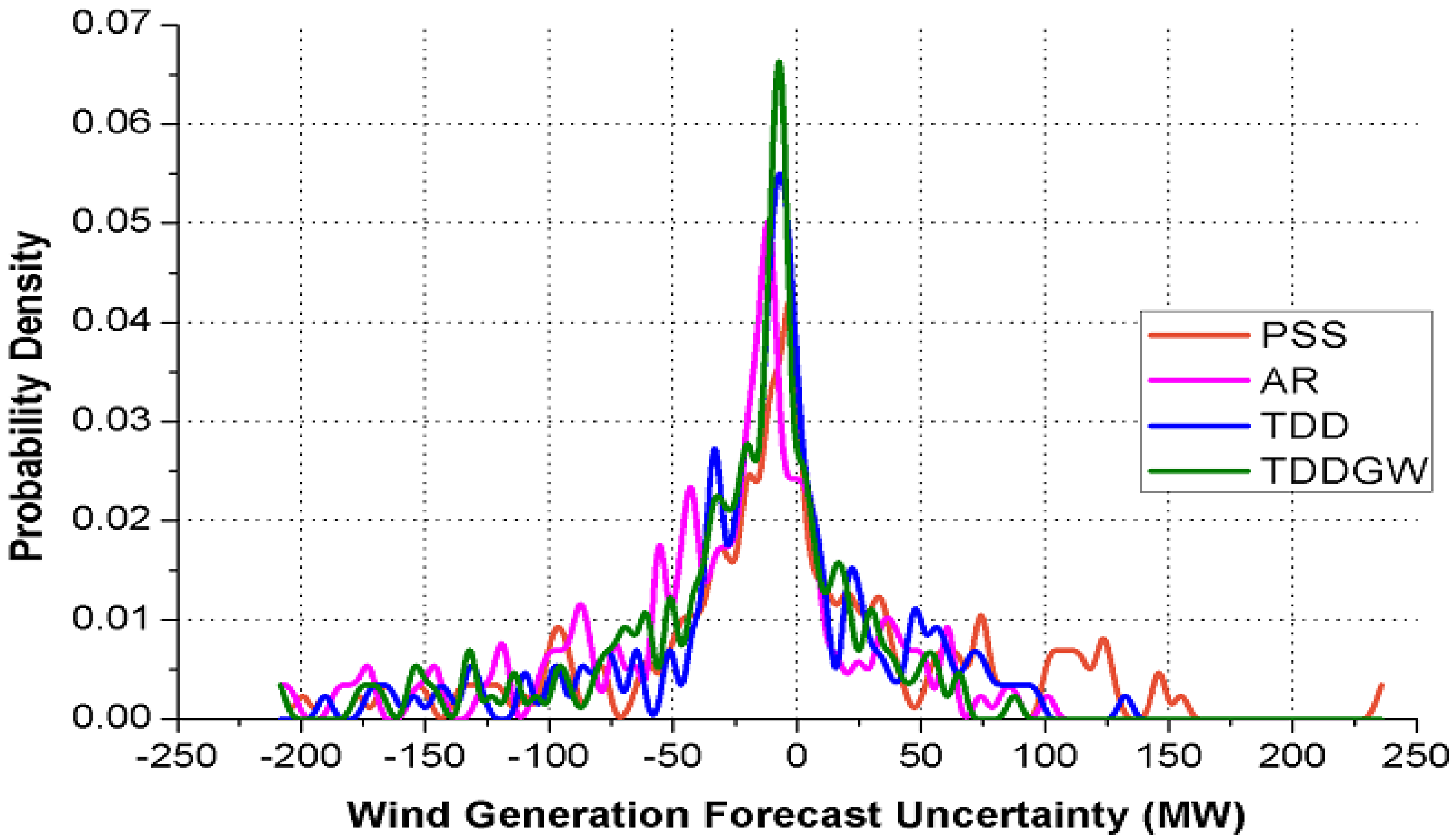
MAE VALUES OF THE 10-MINUTE-AHEAD, 20-MINUTE-AHEAD AND UP TO 1-HOUR-AHEAD FORECASTS ON 11 DAYS' IN 2010 FROM THE PSS, AR, TDD AND TDDGW MODELS AT THE FOUR LOCATIONS (SMALLEST IN BOLD)

Location	Model	10 min	20 min	30 min	40 min	50 min	60 min
PICT	PSS	0.56	0.72	0.84	0.92	1.00	1.08
	AR	0.55	0.70	0.80	0.87	0.94	1.00
	TDD	**0.54**	**0.68**	**0.77**	0.84	0.90	0.95
	TDDGW	**0.54**	**0.68**	**0.77**	**0.83**	**0.89**	**0.94**
JAYT	PSS	0.50	0.63	0.71	0.78	0.83	0.89
	AR	0.48	0.60	0.68	0.75	0.8	0.86
	TDD	**0.47**	**0.57**	**0.64**	0.69	0.73	0.78
	TDDGW	**0.47**	**0.57**	**0.64**	**0.68**	**0.71**	**0.75**
SPUR	PSS	0.51	0.64	0.73	0.81	0.86	0.92
	AR	0.49	0.61	0.69	0.76	0.80	0.86
	TDD	**0.48**	**0.59**	**0.67**	0.72	0.76	0.81
	TDDGW	0.49	**0.59**	**0.67**	**0.71**	**0.75**	**0.79**
ROAR	PSS	0.55	0.71	0.82	0.92	0.98	1.02
	AR	**0.54**	0.68	0.78	0.86	0.92	0.96
	TDD	**0.54**	**0.67**	0.77	0.85	0.90	0.93
	TDDGW	**0.54**	**0.67**	**0.76**	**0.82**	**0.87**	**0.90**

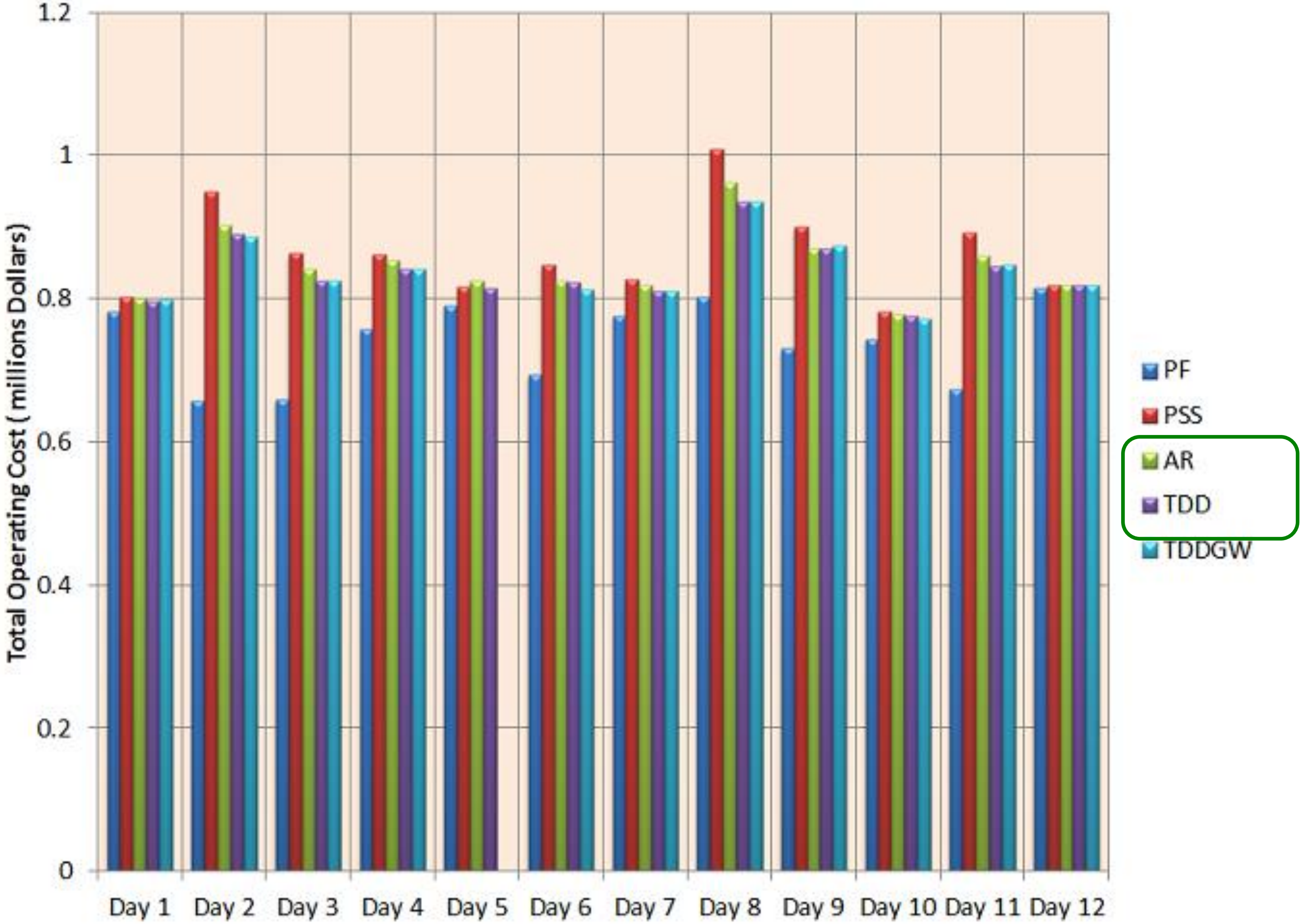
Wind Generation Forecast Distribution

One Hour-ahead Wind Generation Forecast Uncertainty

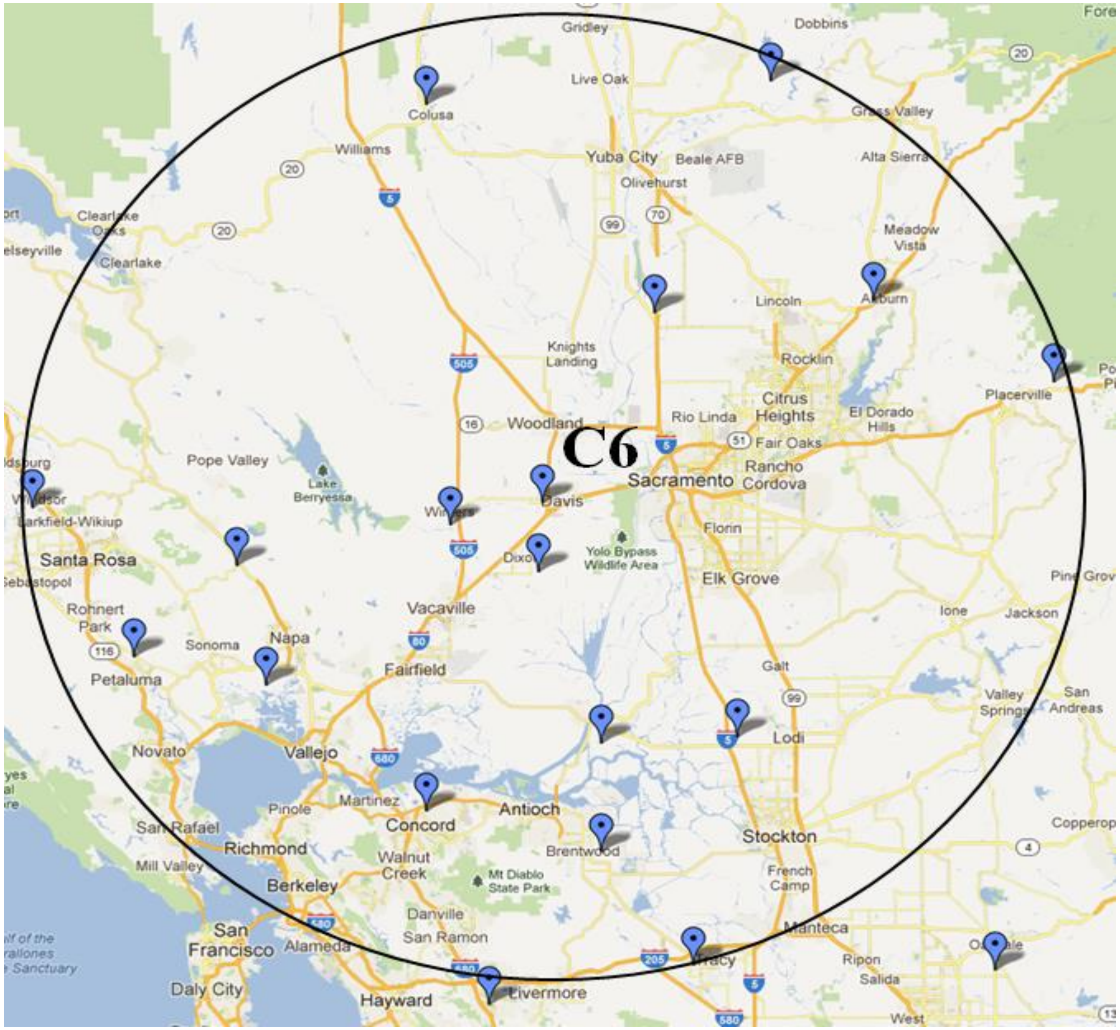
Hour ahead Wind generation forecast uncertainties of Jayton (JAYT), Texas under various days



Total Operating Cost



Spatio-temporal Solar Forecast [2]



[2] C. Yang, A. Thatte, and L. Xie, “Multi time-Scale Data-Driven Spatio-Temporal Forecast of Photovoltaic Generation,” IEEE Tran. Sustainable Energy, 2015.

ARX Model for Solar Irradiance Forecast [2]

$$
\begin{aligned}
y[t] = f(&y[t-1], \ldots, y[t-n], \\
&u_1[t-d_1], \ldots, u_1[t-d_1-m_1+1], \\
&\vdots \\
&u_i[t-d_i], \ldots, u_i[t-d_i-m_i+1])
\end{aligned}
$$

Local

Neighbor Sites

We compared our model (ST) to persistence (PSS), auto regression (AR), and back-propagation neural network (BPNN) forecast models

[2] C. Yang, A. Thatte, and L. Xie, "Multi time-Scale Data-Driven Spatio-Temporal Forecast of Photovoltaic Generation," IEEE Tran. Sustainable Energy, 2015.

Results [2]

Case Number	Training Period	Validation Period
1	January, March, May, July, September, November	February, April
2		April, June
3		June, August
4		August, October

Performance for 1 hour ahead

	Case 1				Case 2			
Index	ST	AR	BPNN	PSS	ST	AR	BPNN	PSS
MAE	58.3	62.0	99.1	92.7	52.1	54.4	97.8	102.0
RMSE	81.5	87.0	137.6	116.2	78.3	84.0	139.3	124.8
	Case 3				Case 4			
Index	ST	AR	BPNN	PSS	ST	AR	BPNN	PSS
MAE	52.1	54.4	68.5	102.0	29.2	31.0	63.8	94.0
RMSE	78.3	84.0	97.8	124.8	43.4	45.8	87.3	109.5

Performance for 2 hour ahead

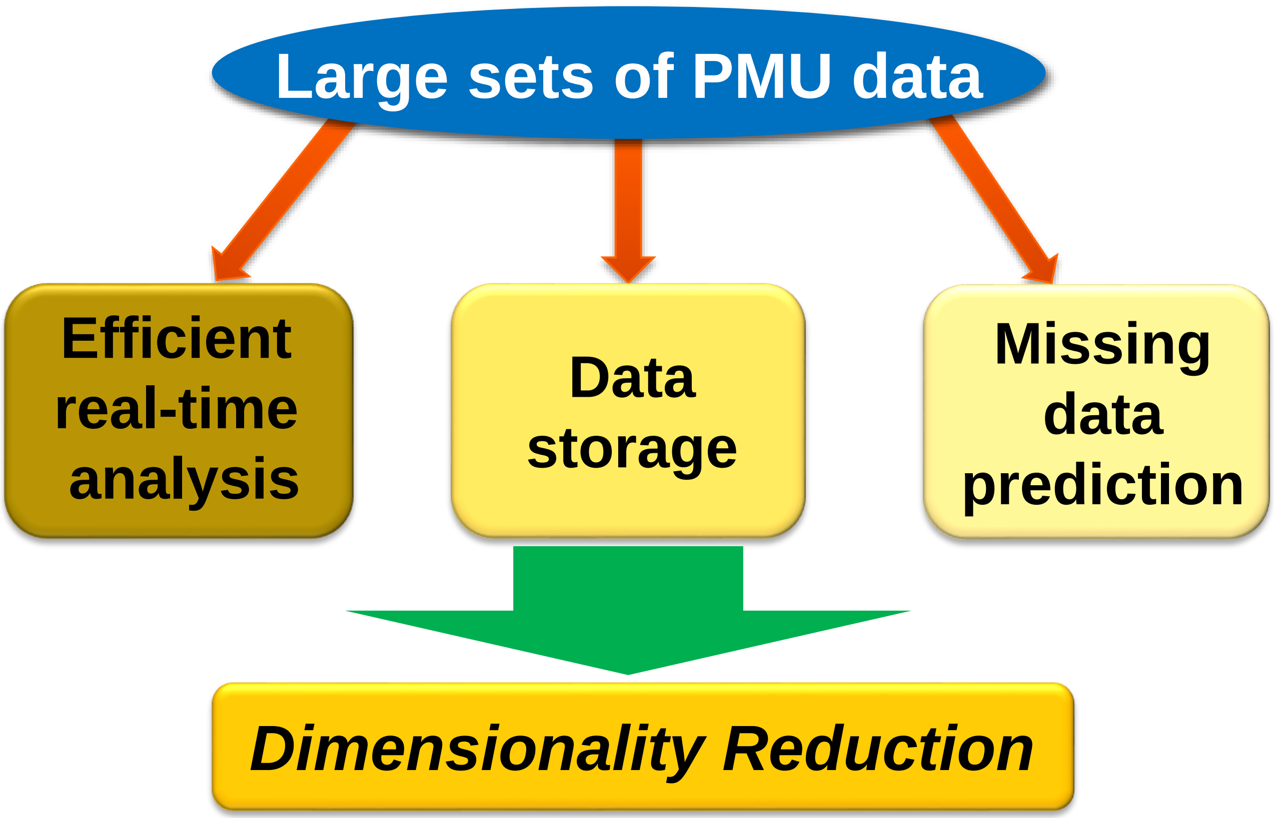
	Case 1				Case 2			
Index	ST	AR	BPNN	PSS	ST	AR	BPNN	PSS
MAE	100.0	107.9	148.1	160.3	83.4	90.5	145.9	173.5
RMSE	136.3	143.7	198.7	200.3	122.9	132.2	200.0	207.3
	Case 3				Case 4			
Index	ST	AR	BPNN	PSS	ST	AR	BPNN	PSS
MAE	34.7	39.7	103.9	163.6	41.3	44.0	93.7	153.8
RMSE	49.9	58.7	138.1	182.0	58.3	63.4	118.2	175.1

Shorter time-scale: Spatio-temporal is worse than PSS

Part I: Summary

- Spatio-temporal correlation among renewable generation sites (wind and photovoltaic) could be leveraged for improved near-term forecast
- The economic benefit from spatio-temporal forecast vary at different time scales
- Possible extensions:
  - Large ramp forecast
  - Distributed PV forecast

Barriers to Using PMU for Real-time Operations

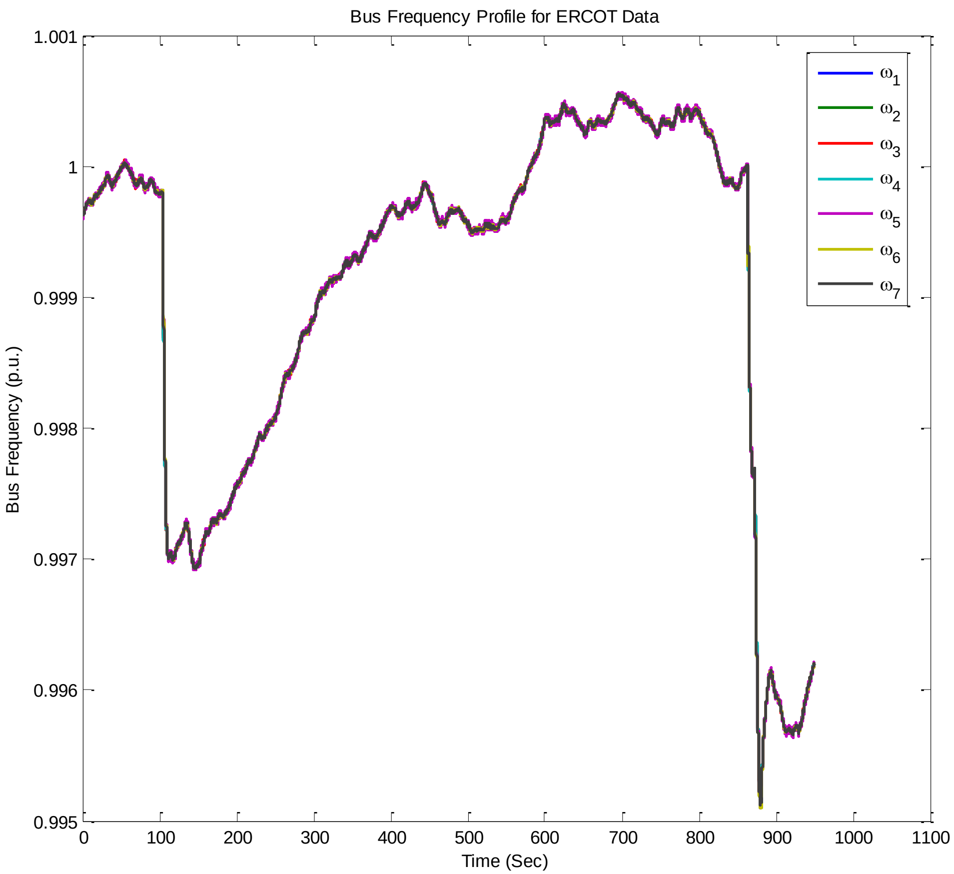


Related Work:

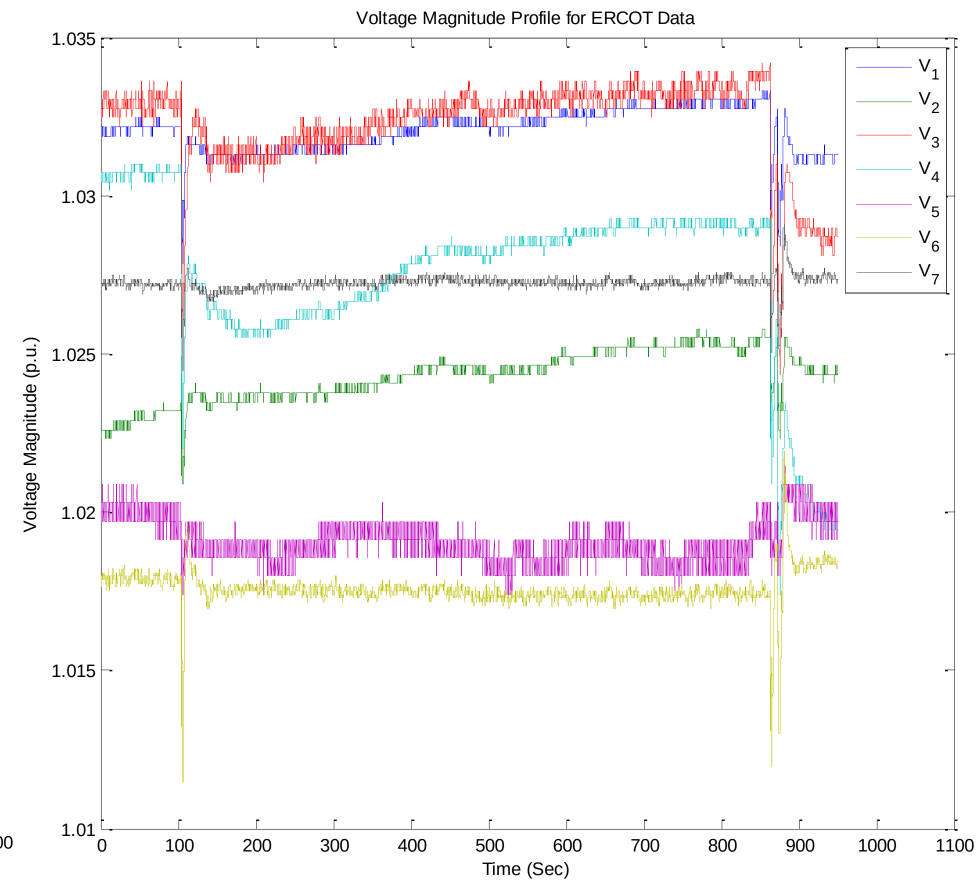
[5] M. Wang, J.H. Chow, P. Gao, X.T. Jiang, Y. Xia, S.G. Ghiocel, B. Fardanesh, G. Stefopolous, Y. Kokai, N. Saito, M. Razanousky, "A Low-Rank Matrix Approach for the Analysis of Large Amounts of Power System Synchrophasor Data," in System Sciences (HICSS), 2015.

[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.

Raw PMU Data from Texas



Bus Frequency Profile

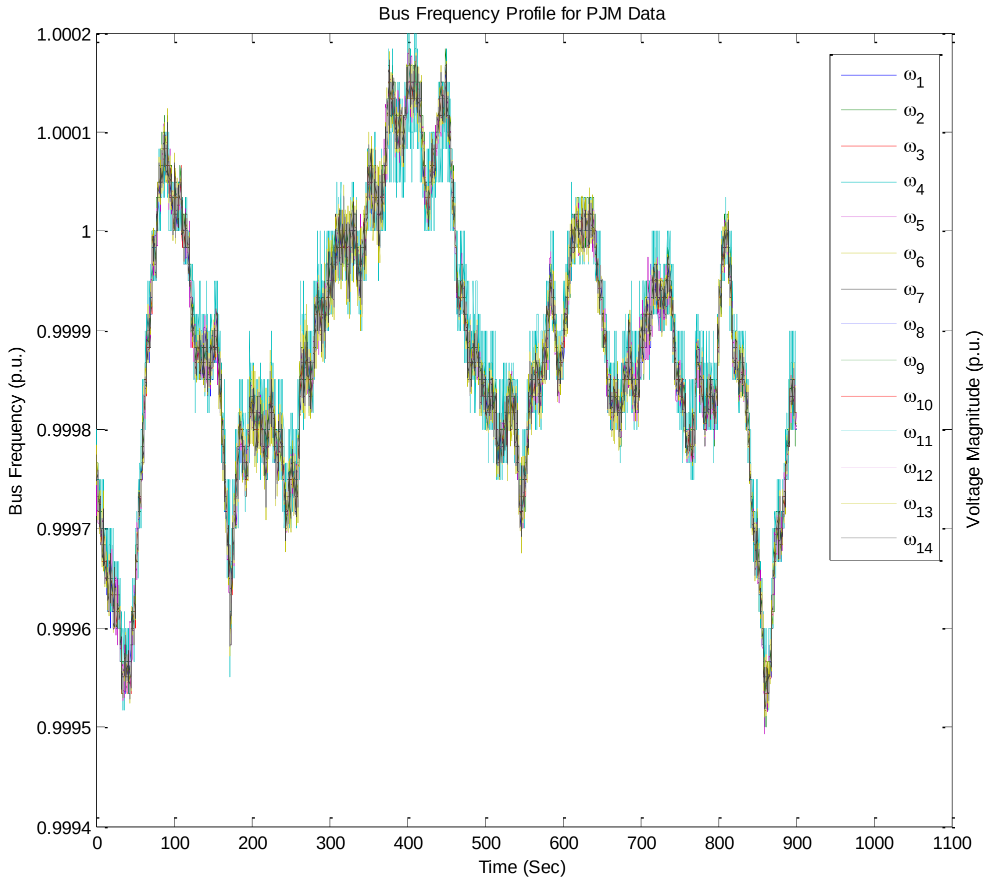


Voltage Magnitude Profile

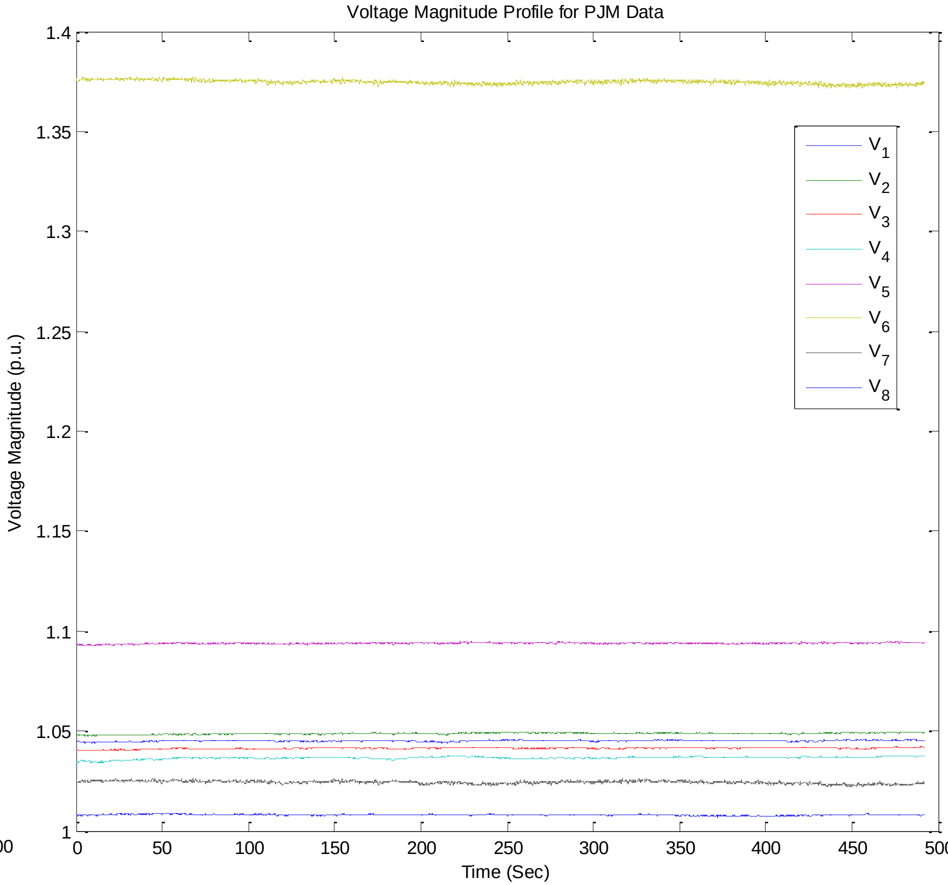
No system topology, no system model.

Total number of PMUs: 7.

PMU Data from Eastern Interconnection



Bus Frequency Profile



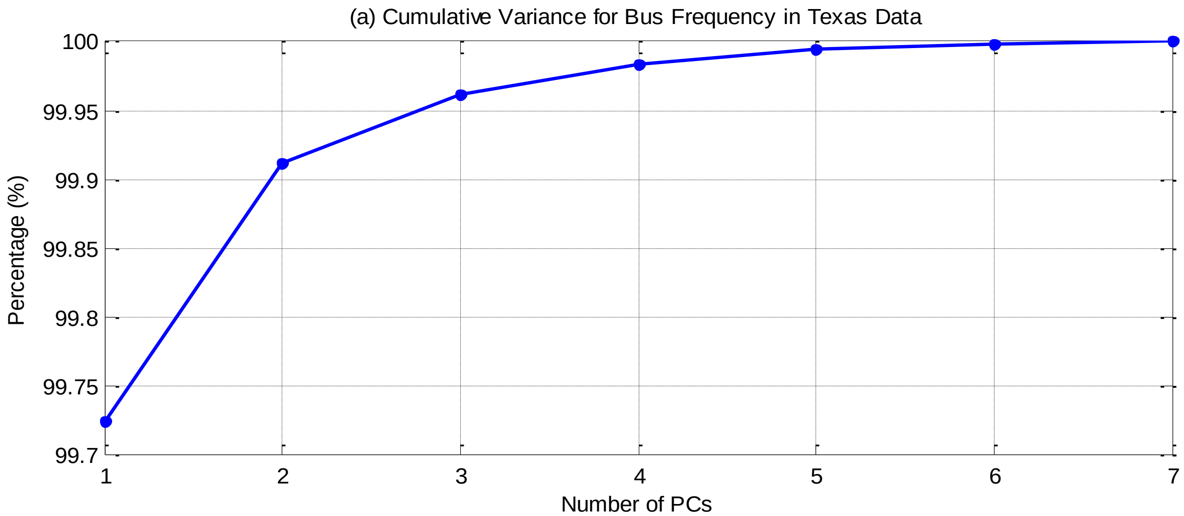
Voltage Magnitude Profile

Total number of PMUs: 14 for frequency analysis

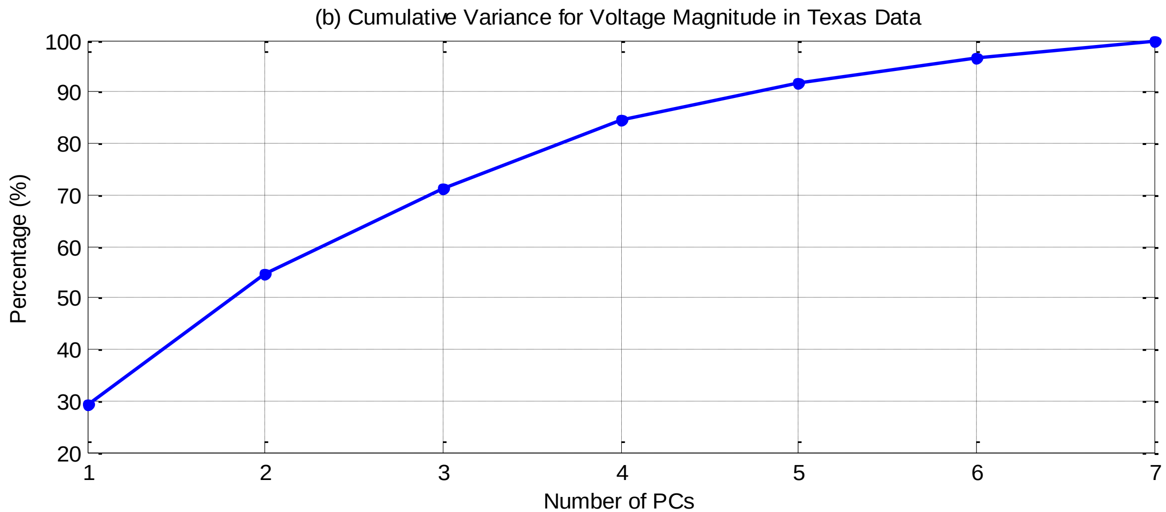
8 for voltage magnitude analysis.

PCA for Texas Data

$$Y_B^{\omega} = [\omega_5,\ \omega_3]$$



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

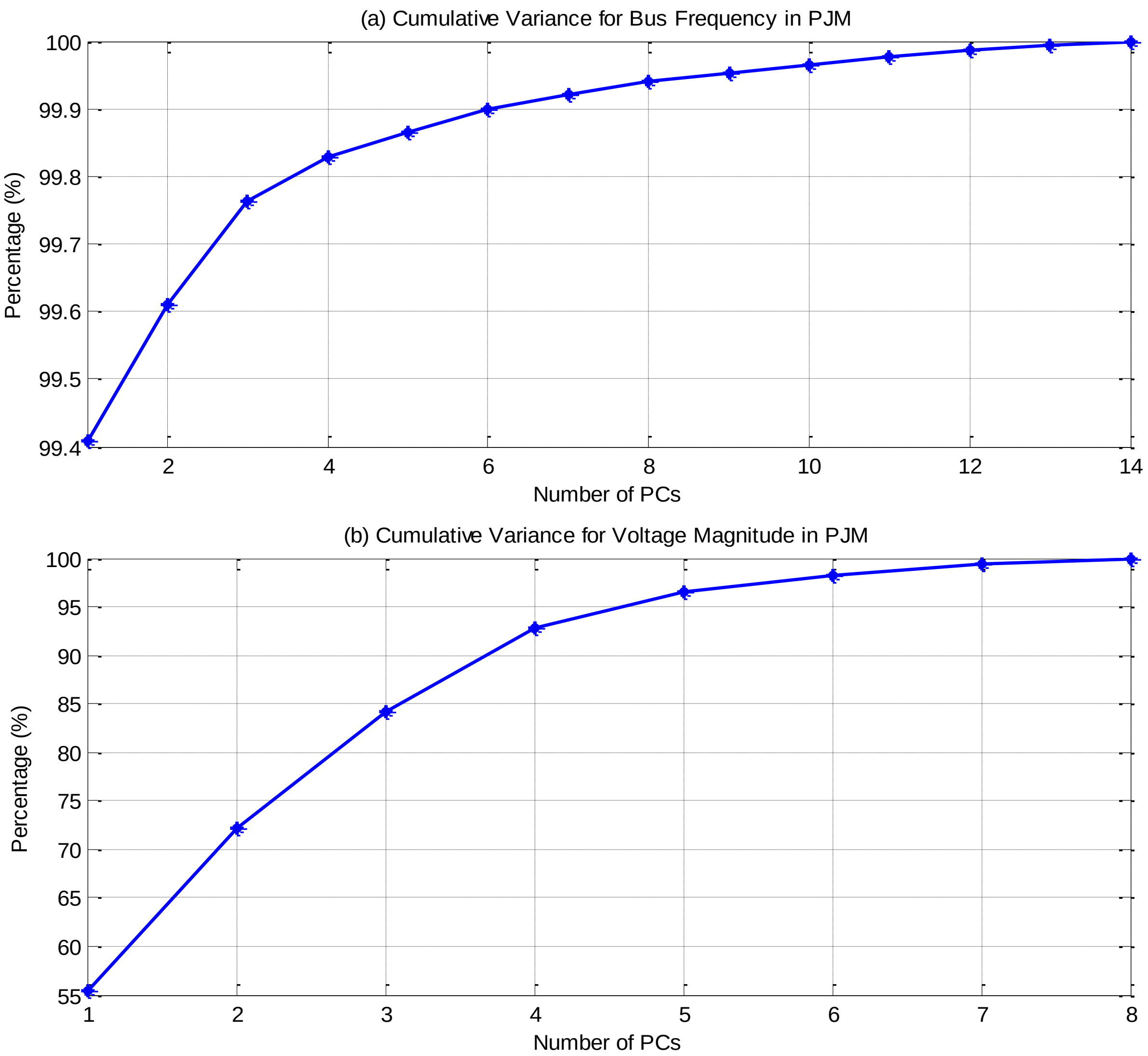


Cumulative variance for bus frequency and voltage magnitude for Texas data.

PCA for Eastern Interconnection

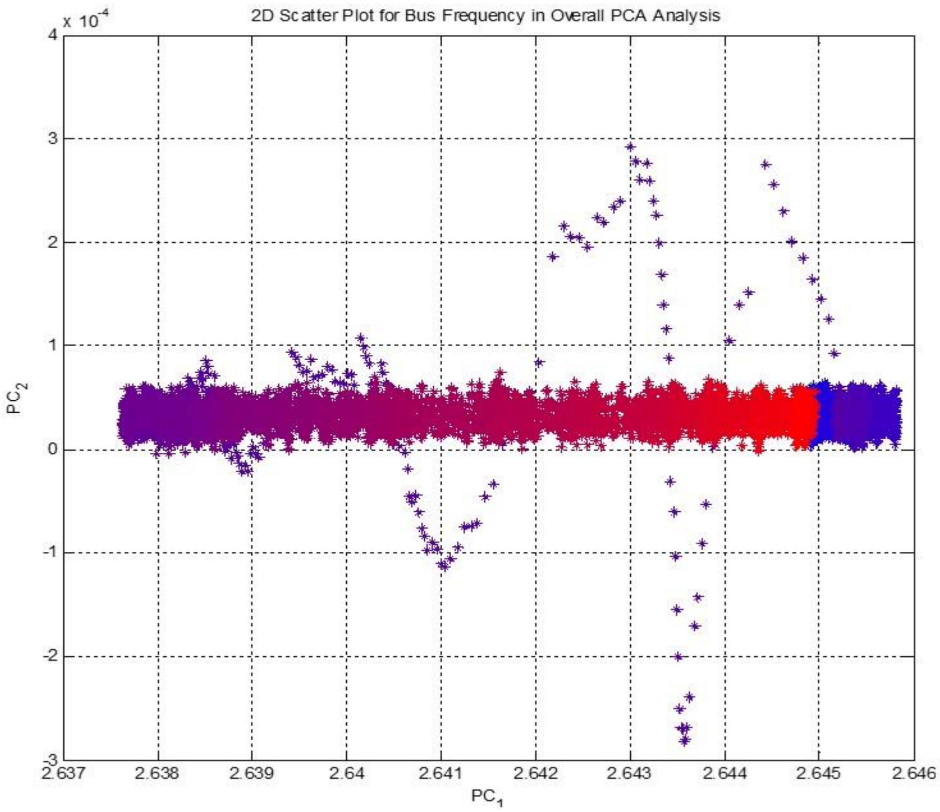
$$Y_B^{\omega} = [\omega_{11},\ \omega_6]$$

$$Y_B^{V} = [V_8,\ V_5,\ V_2]$$

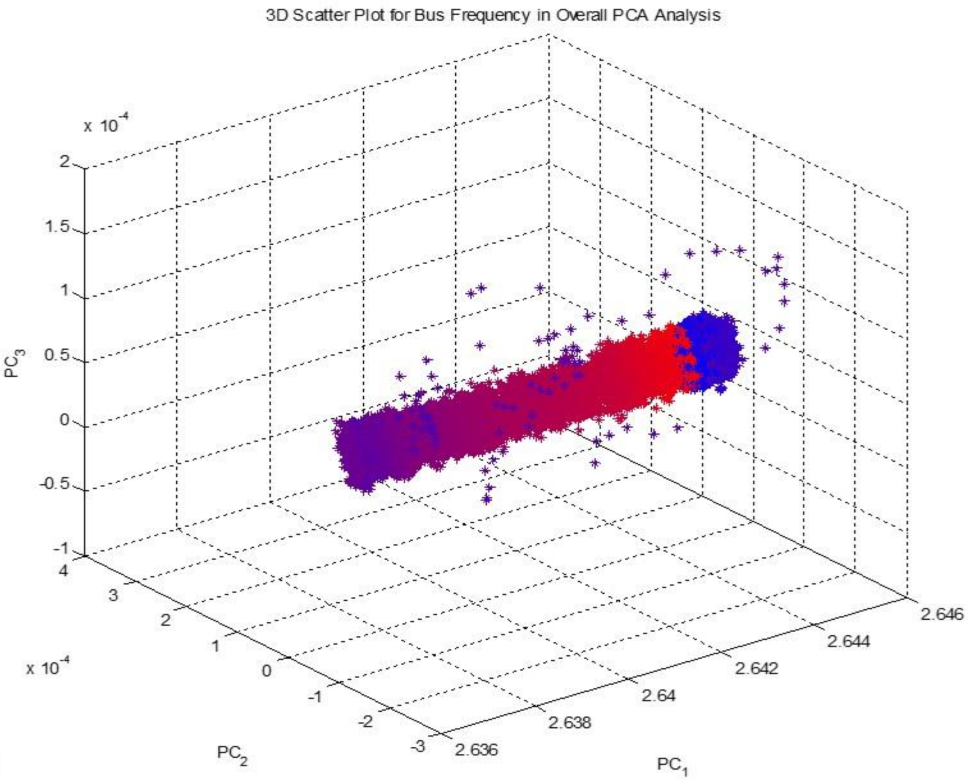


Cumulative variance for bus frequency and voltage magnitude for PJM data.

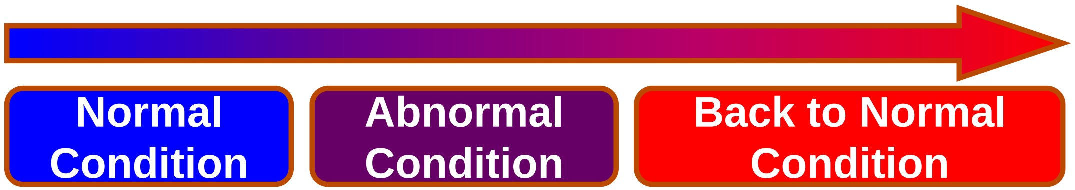
Scatter Plot of Bus Frequency



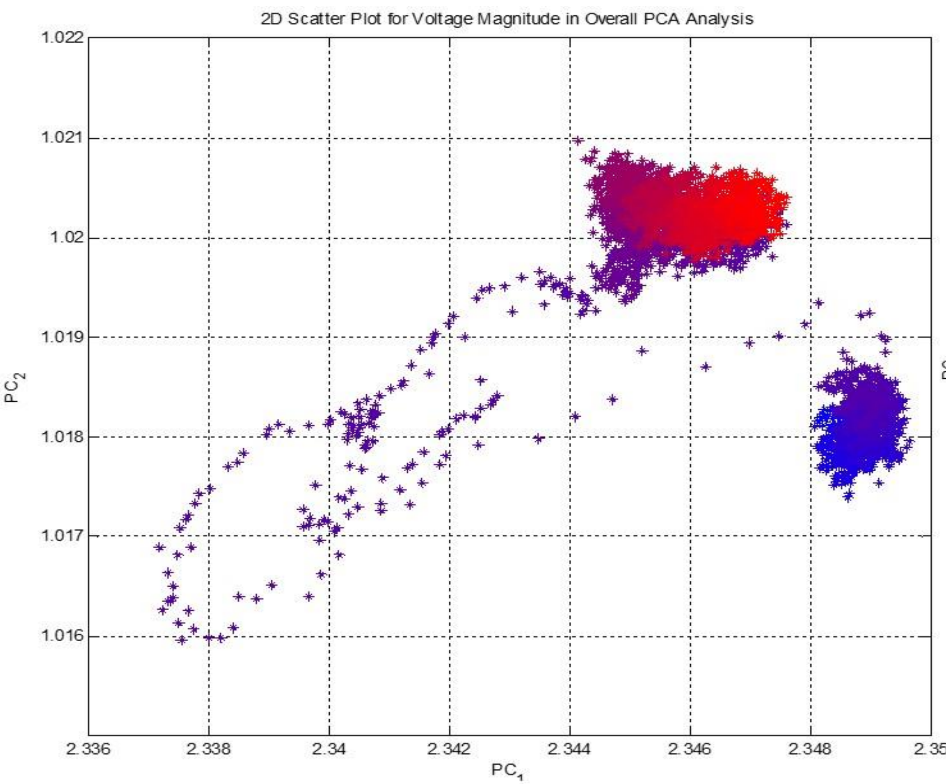
2D Scatter plot for bus frequency.



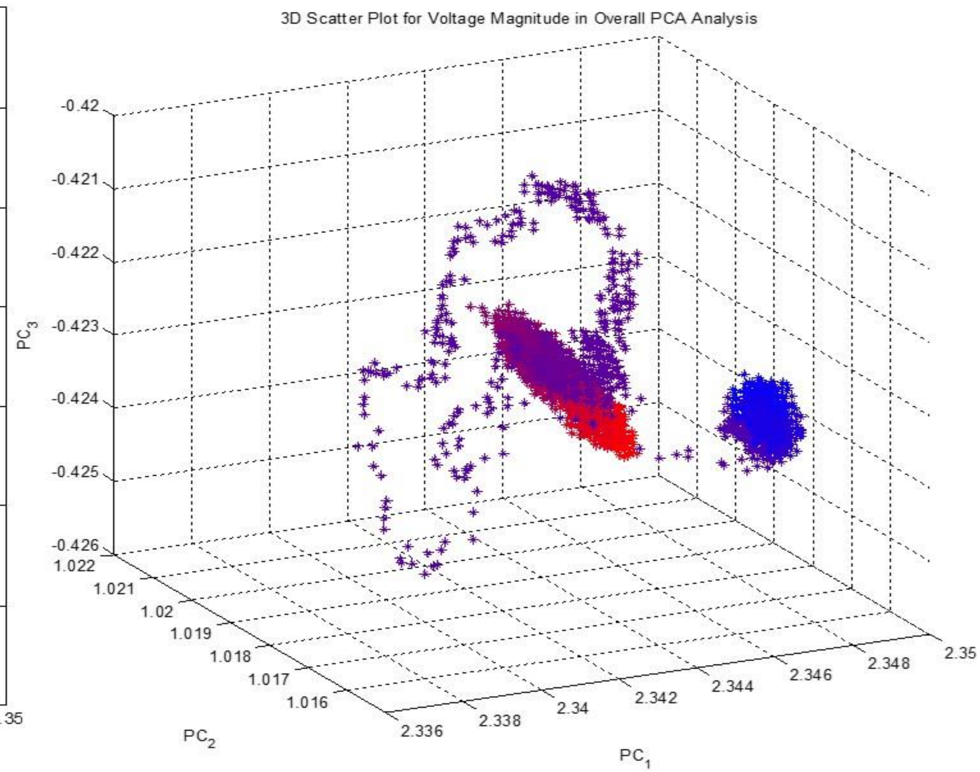
3D Scatter plot for bus frequency.



Scatter Plot of Voltage Magnitude



2D Scatter plot for voltage magnitude.



3D Scatter plot for voltage magnitude.

Normal Condition | **Abnormal Condition** | **Back to Normal Condition**

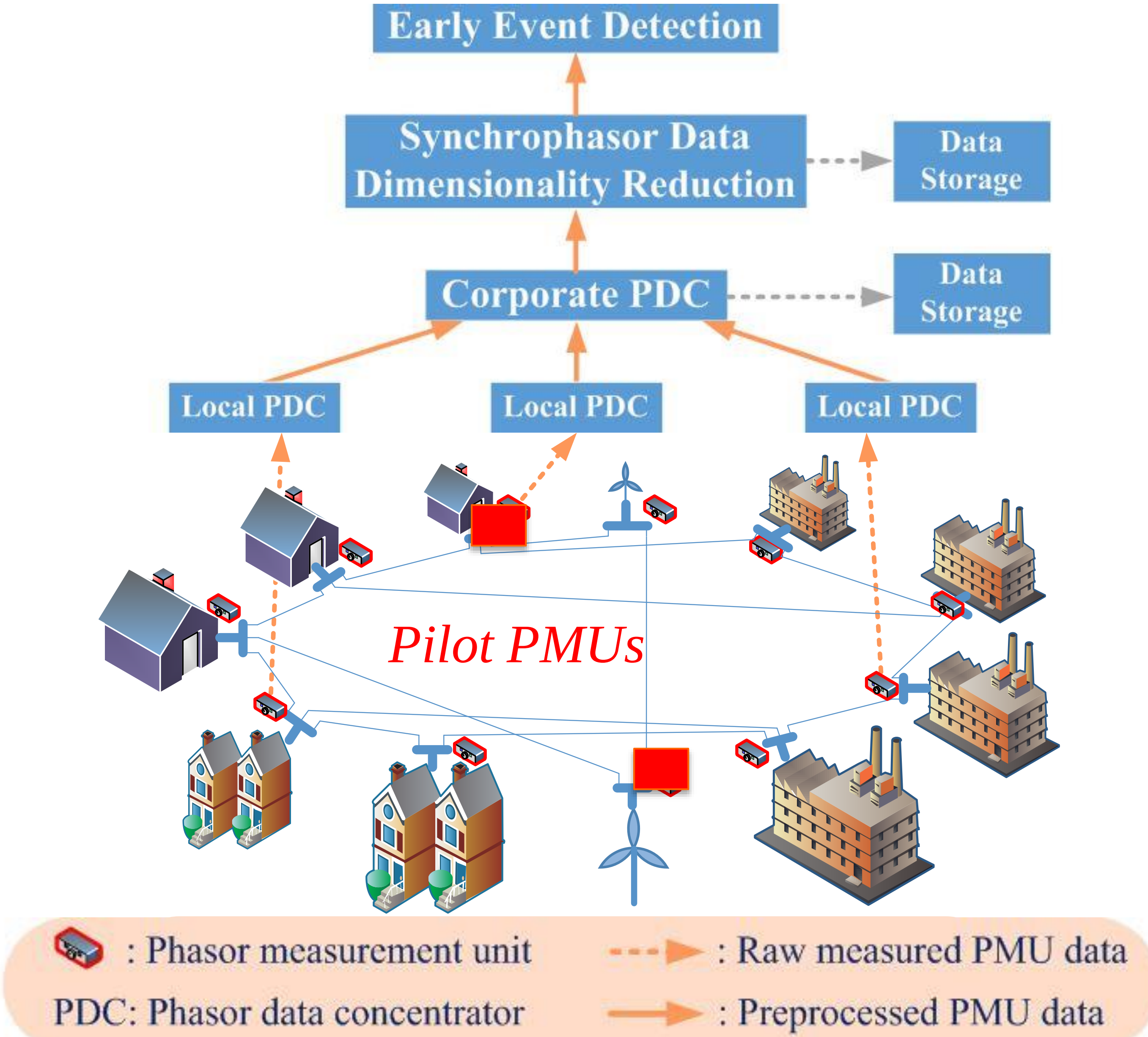
Observations

- 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

Early Event Detection



Dimensionality Reduction Algorithm [3]

1. PMU Data Collection : Measurement matrix

$$Y_{n\times N} = [y^{(1)}, \quad \ldots, \quad y^{(N)}] \qquad y^{(i)} = [y_1^{(i)}, \quad \ldots, \quad y_n^{(i)}]^T$$

N measurements. Each has *n* samples in the time history.

2. PCA-based Dimensionality Reduction

(1) Eigenvalues and eigenvectors of covariance matrix $Cov(Y)$.

(2) Rearrange eigenvalues in decreasing order to find principal components (PCs).

(3) Select top *m* out of *N* PCs based on predefined threshold.

(4) Project original *N* variables in the *m* PC-formed new space.

(5) *m'* variables are kept and chosen as orthogonal to each other as possible.

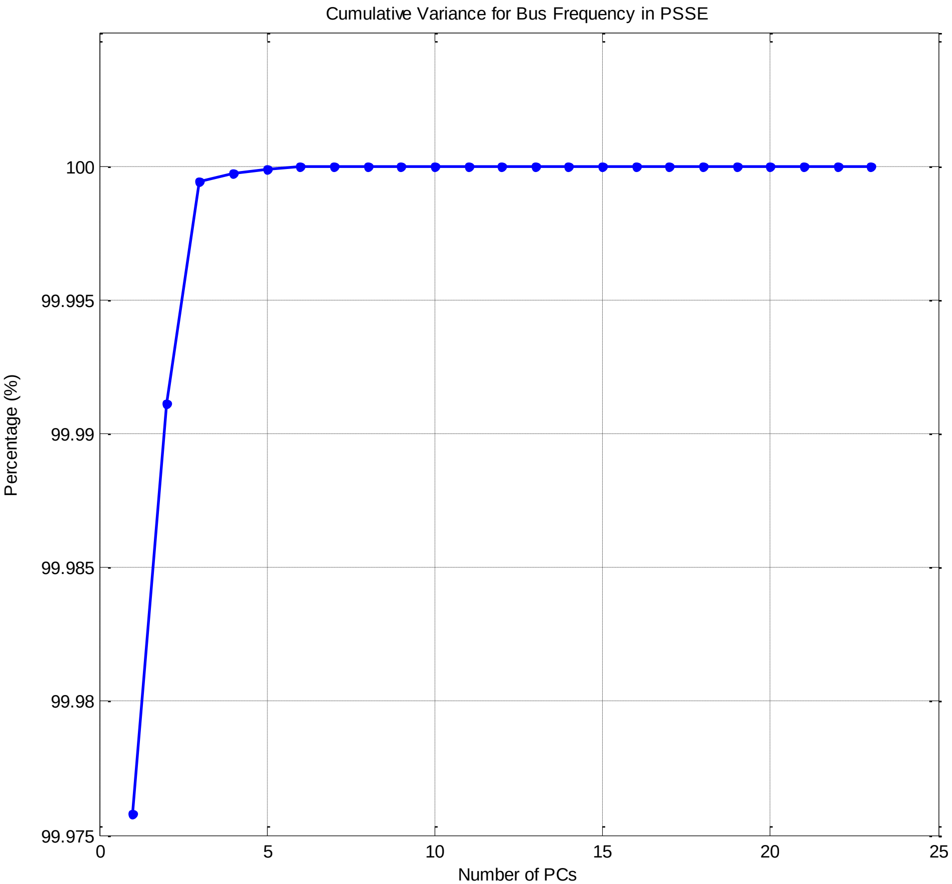
(6) Basis matrix $Y_B := [y_b^{(1)}, \quad \ldots, \quad y_b^{(m')}] \subseteq Y$

(7) Predict $y^{(i)}$ in terms of Y_B

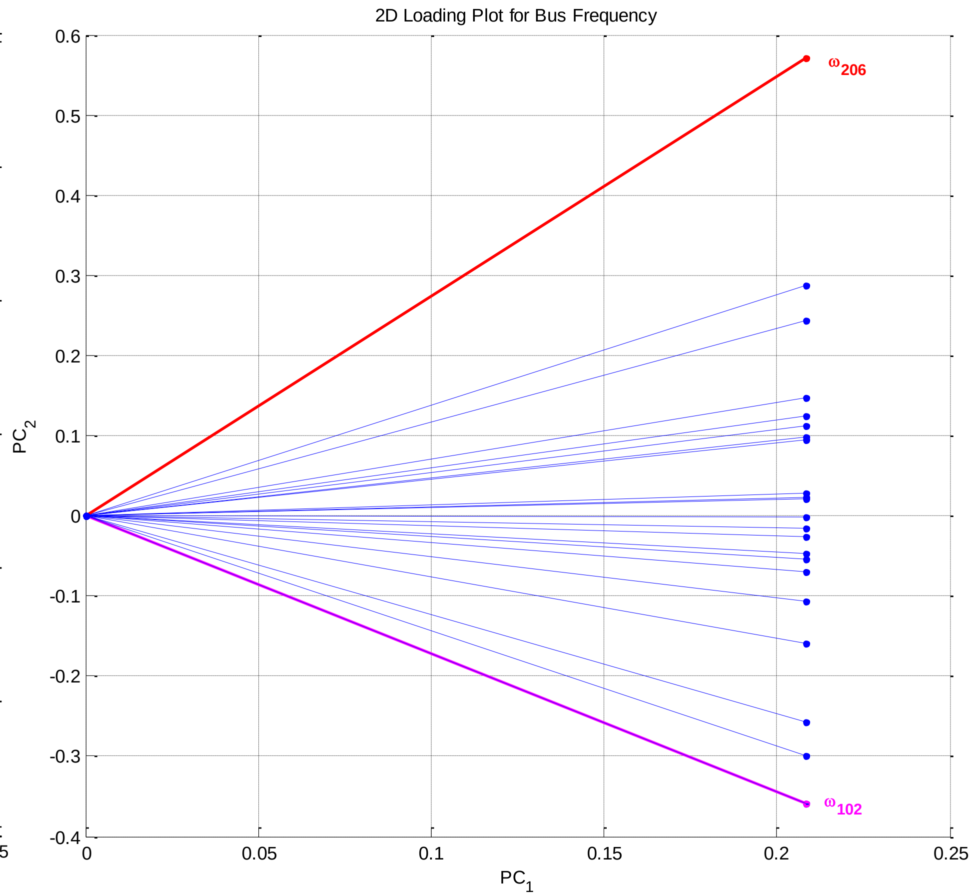
$$\hat{y}^{(i)} \approx \sum_{j=1}^{m'} v_j^{(i)} y_b^{(j)} = Y_B v^{(i)}. \qquad v^{(i)} := \left(Y_B^T Y_B\right)^{-1} Y_B^T y^{(i)}.$$

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

PCA for Bus Frequency



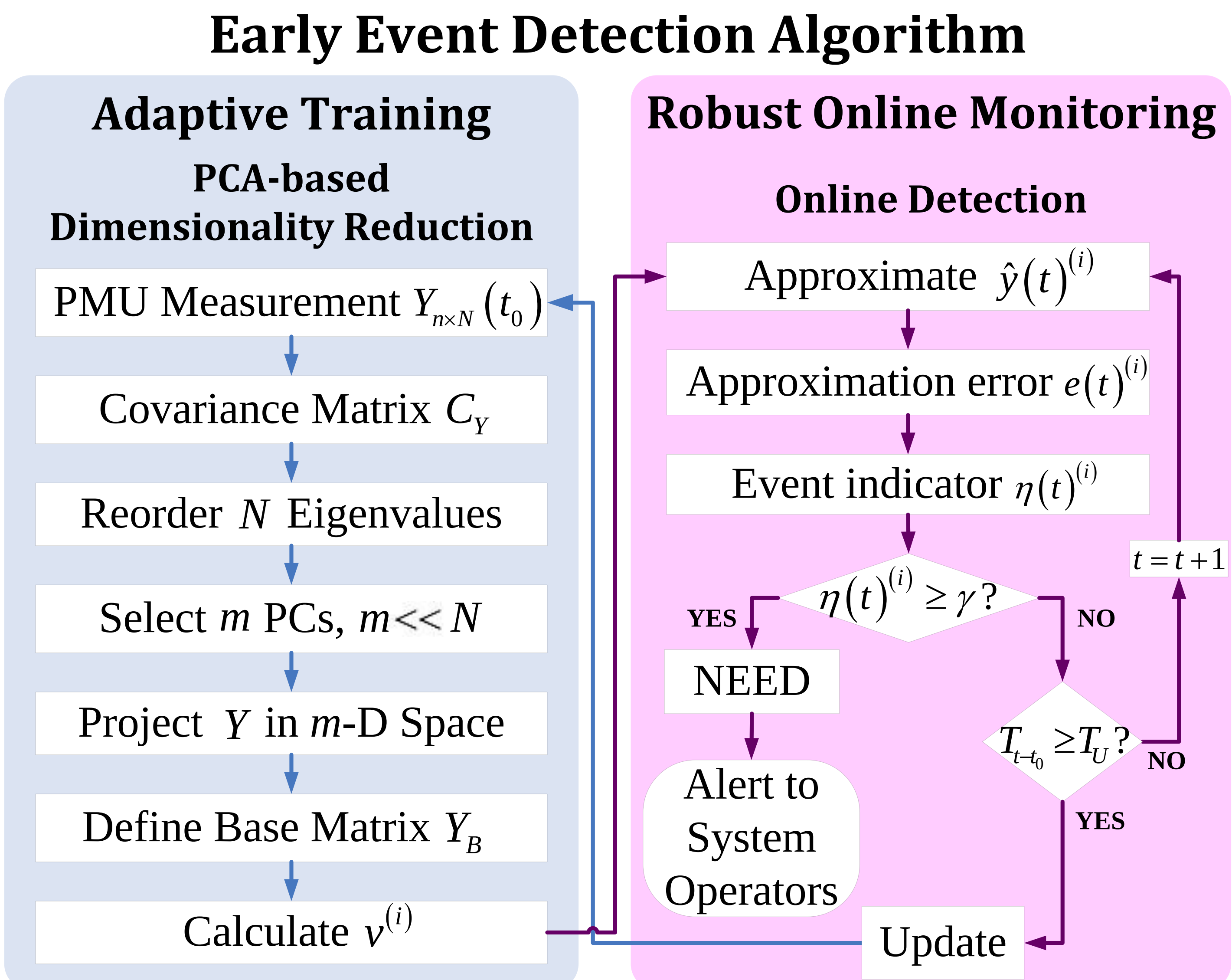
Cumulative variance for bus frequency.



2D Loading plot for bus frequency.

2 PCs. Basis matrix $Y_B^{\omega} = \left[\omega_{206}, \quad \omega_{102}\right]$

Possible Implementation



Theorem for Early Event Detection

Using the proposed *event indicator* η, 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.

Theoretically justified.

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

Sketch of the Proof

- Power system DAE model

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

- Discretization

$$\begin{aligned} x[k+1] &= A_d x[k] + B_d u[k] + \alpha[k], \\ y[k] &= C_d x[k] + D_d u[k] + \varepsilon[k], \end{aligned}$$

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

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

Sketch of the Proof (cont.'d)

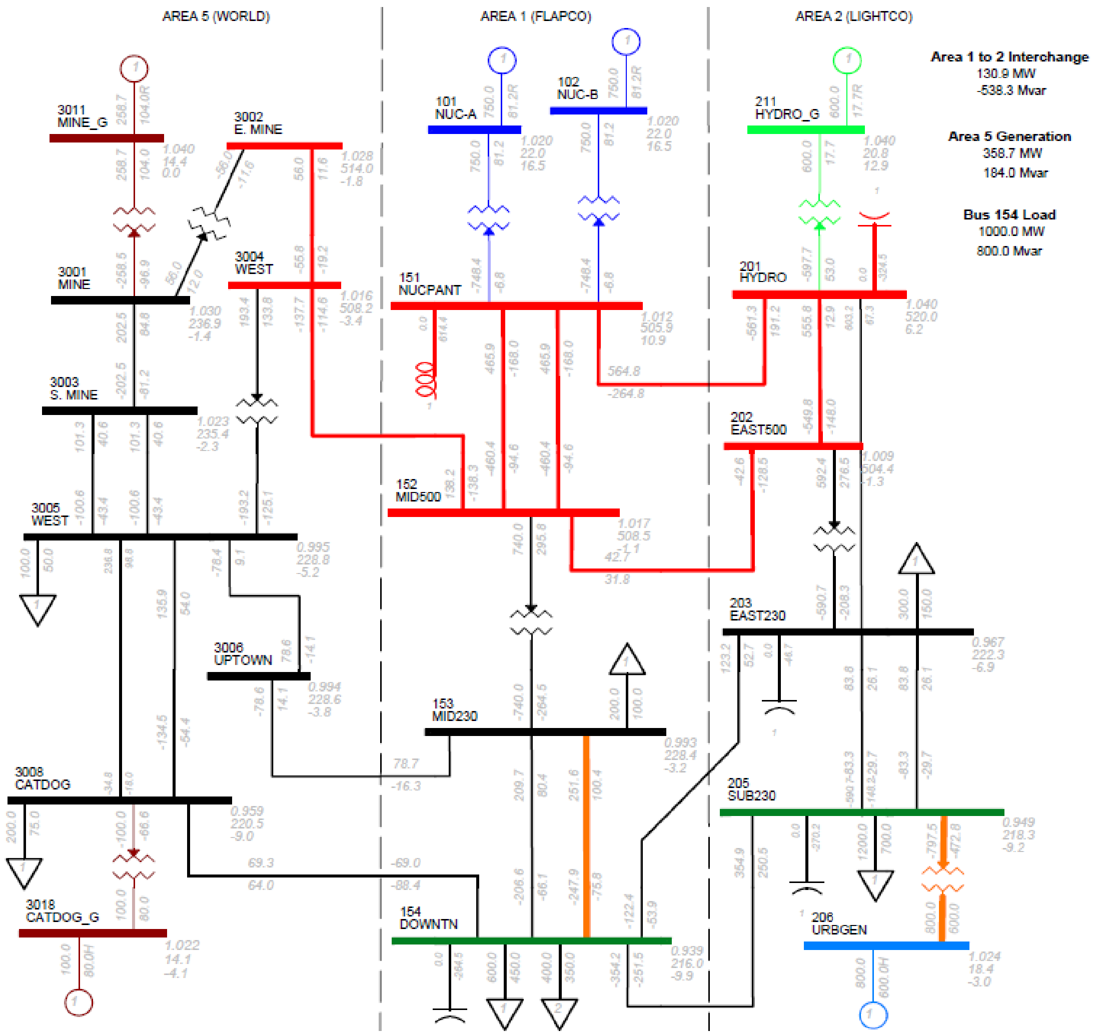
- Normal conditions: training errors are small

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

- 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.

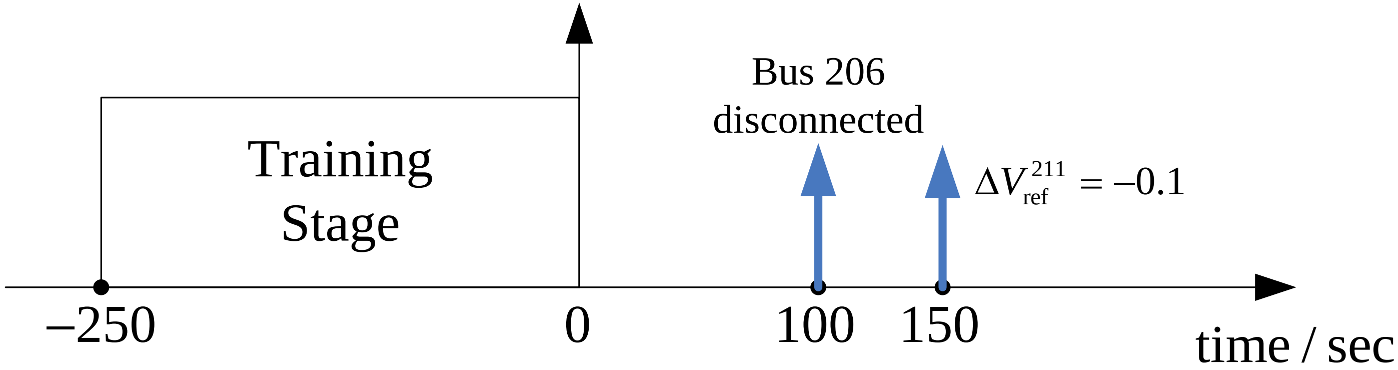
Case Study 1: PSS/E Data

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



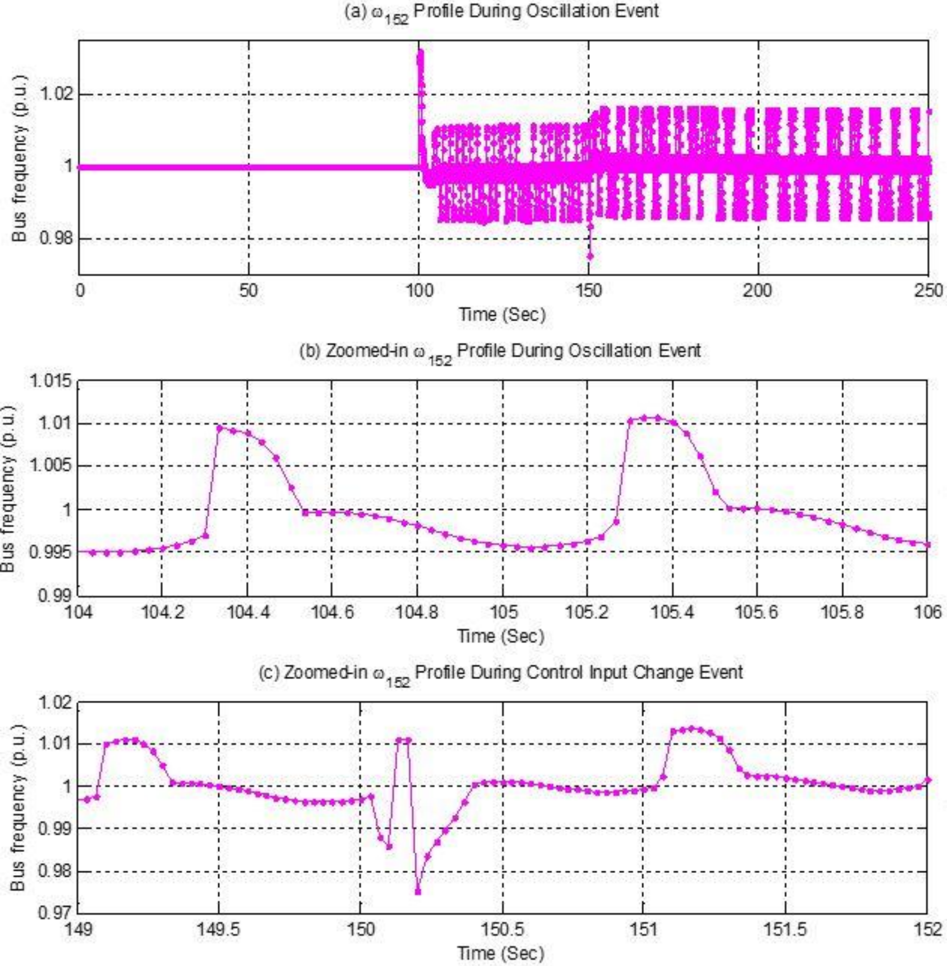
- Siemens, “PSS/E 30.2 program operational manual,” 2009.

Oscillation Event

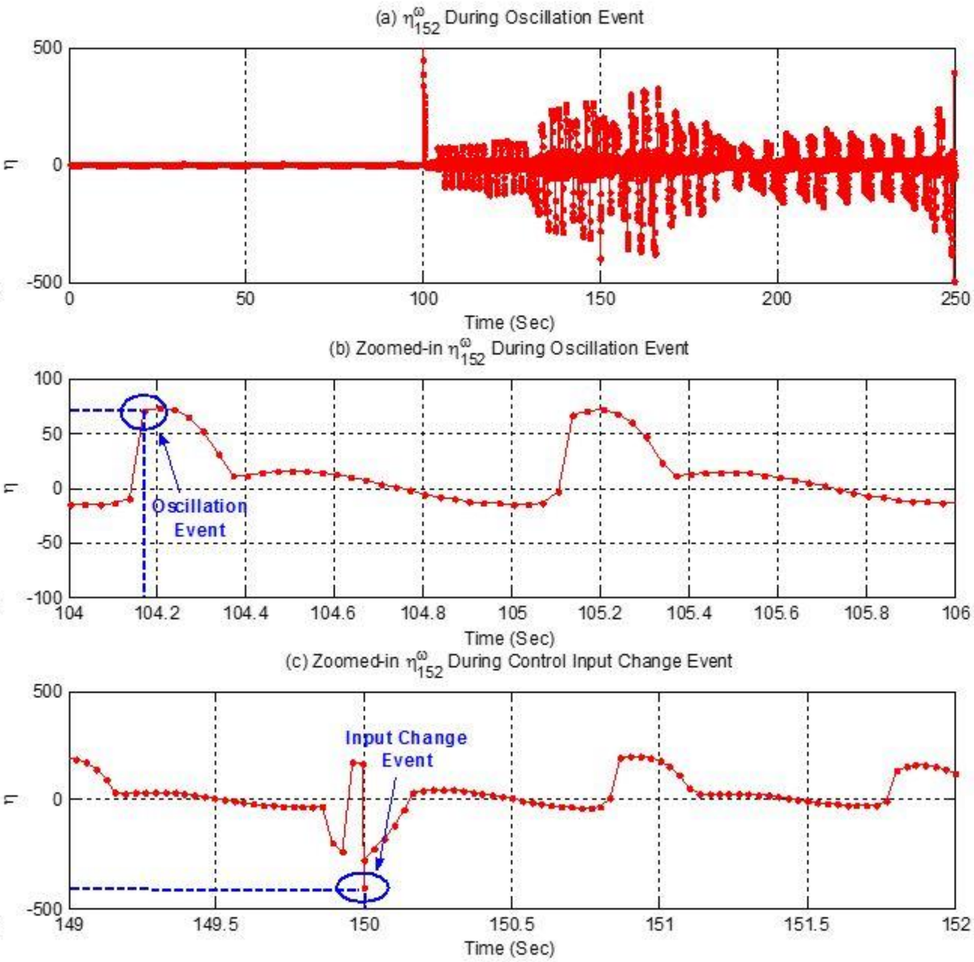


Time	Sampling Points	Event
0-100s	1-3000	Normal Condition
100.03-150s	3001-45000	Bus Disconnection (206)
150.03-250s	4501-7500	Voltage set point changes (211)

Early Event Detection



w152 **profile.**



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

Early Event Detection

- How EARLY is our algorithm?

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

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

- V. Venkatasubramanian, “Oscillation monitoring system, ” PSERC Report, 2008.

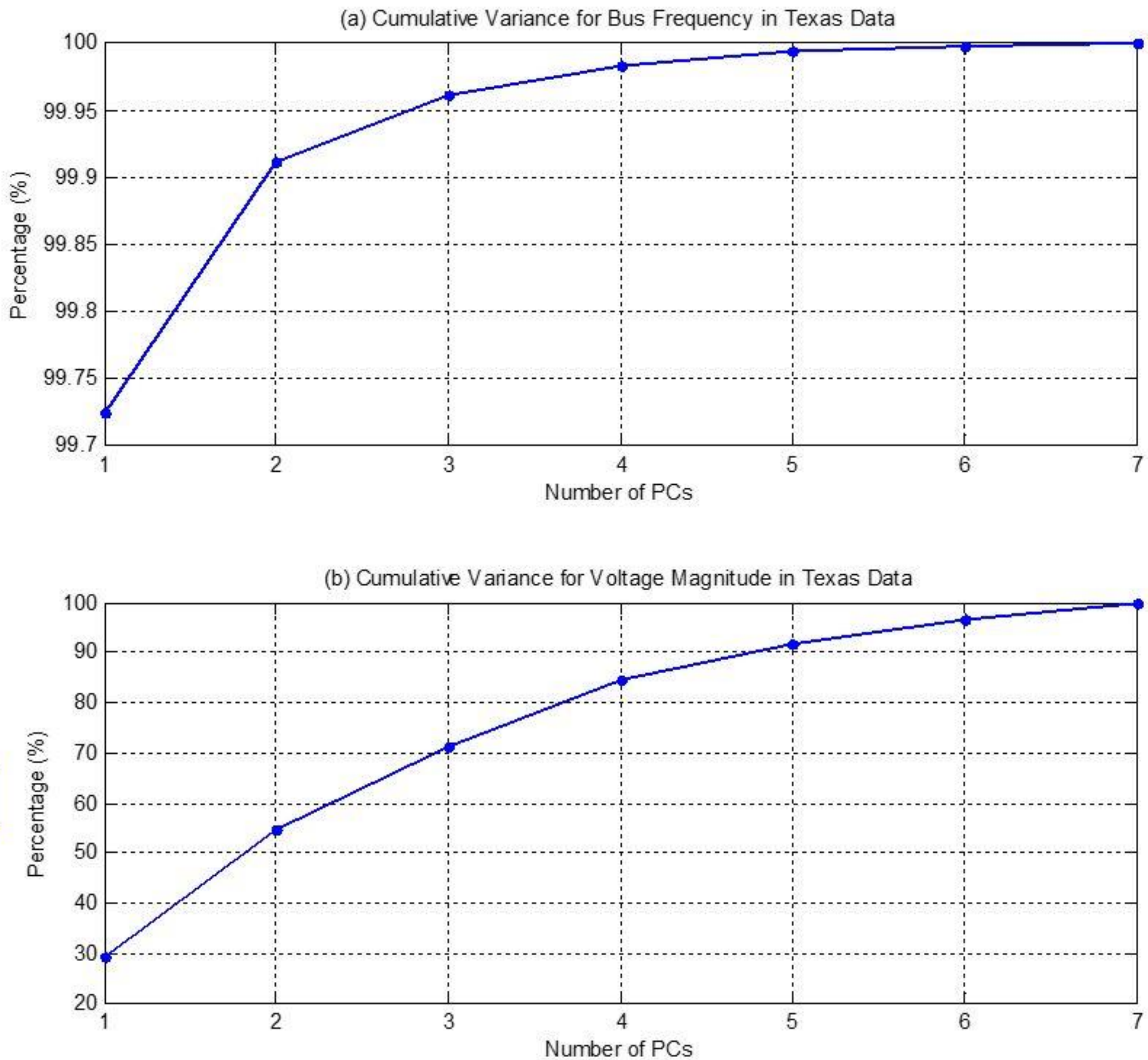
Case Study 2: Unit Tripping Event

- No system topology, no system model.
- Total number of PMUs: 7.
- 2 unit tripping events.
- Sampling rate: 30 Hz.

PCA for Bus Frequency and Voltage Magnitude

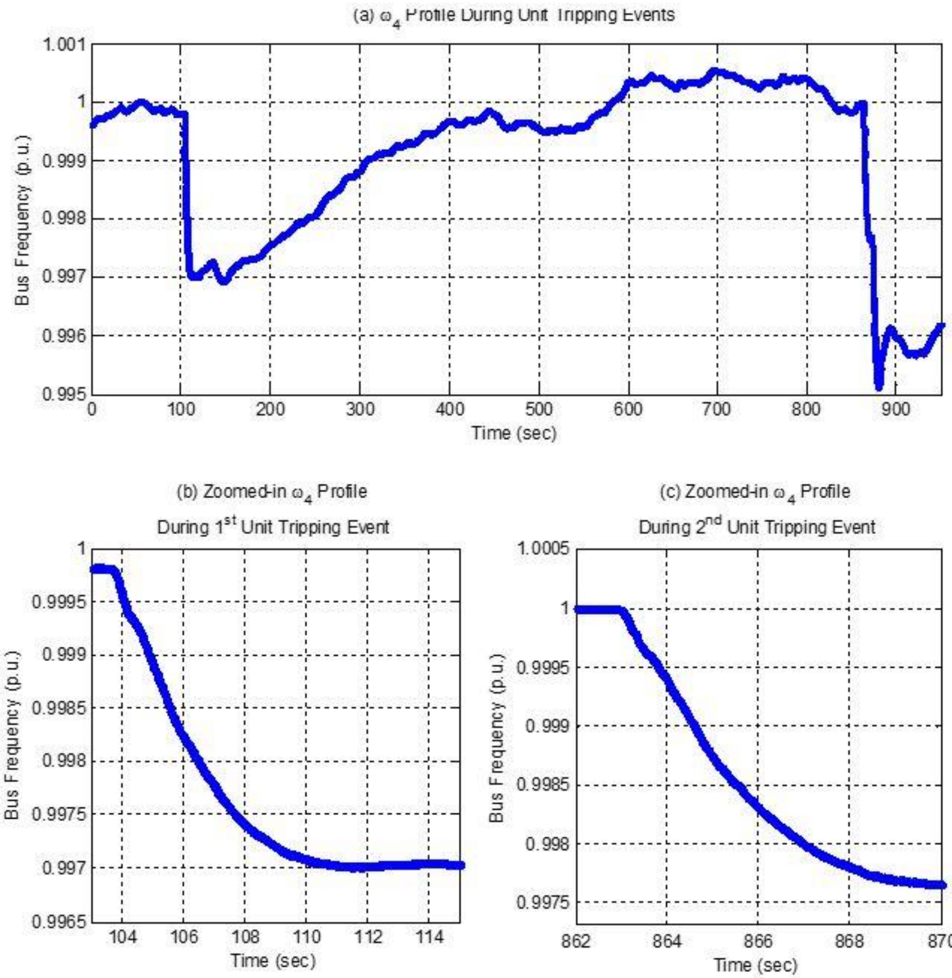
$$Y_B^{\omega} = [\omega_5,\ \omega_3]$$

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

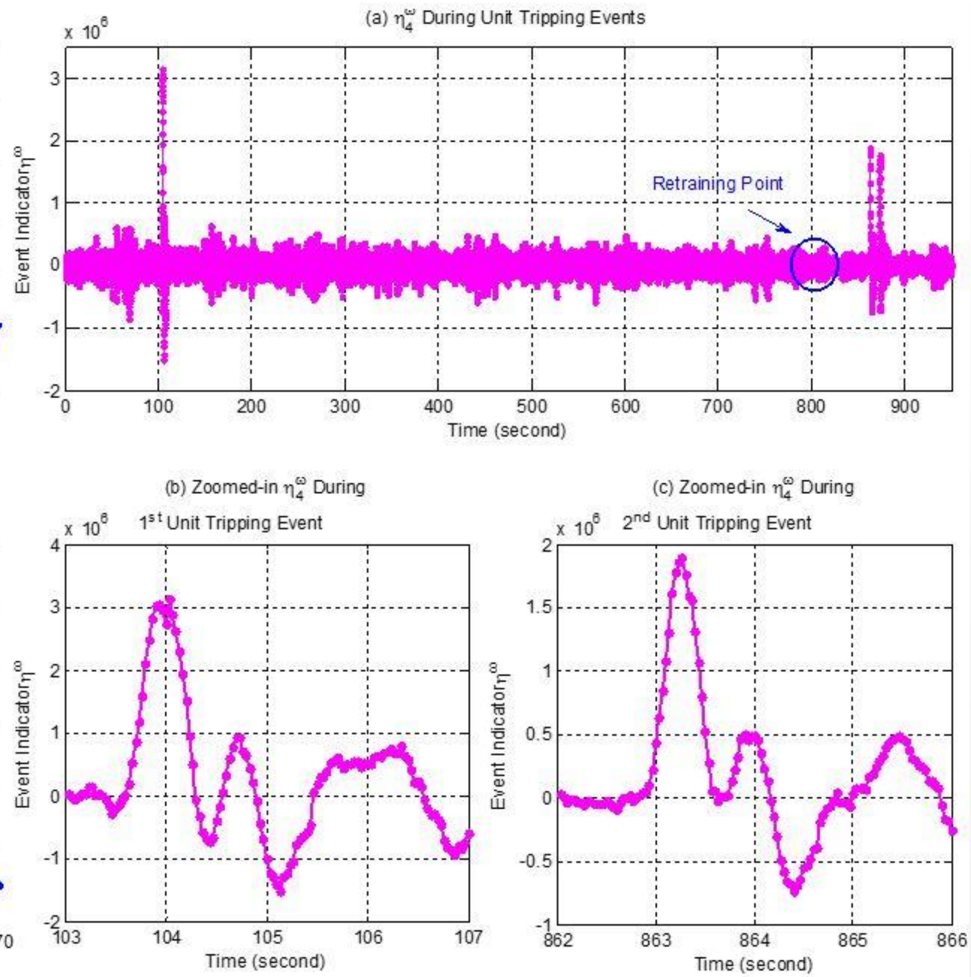


Cumulative variance for bus frequency and voltage magnitude for Texas data.

Early Event Detection



w4 **profile.**



η_4^{ω} **during unit tripping event.**

Part II: Summary

- Large-scale PMU data can be reduced to a space with much lower dimensionality (surprisingly well).
- Change of dimensionality could be leveraged for novel early anomaly detection
- Rich physical insights can be obtained from PMU data
- Possible extensions:
  - Event classification, specification and localization
  - Online PMU bad data processing

- Y. Chen, L. Xie, and P. R. Kumar, “Power system event classification via dimensionality reduction of synchrophasor data,” in Sensor Array and Multichannel Signal Processing Workshop, 2014. SAM 2014

Concluding Remarks

- We investigated the integration of large data sets for improved grid operations:
  - Spatio-temporal analytics for improved renewable forecast & market operations
  - Dimensionality reduction of synchrophasor data for improved monitoring and anomaly detection
- Many open questions
  - Streaming data quality
  - Data analytics integration with EMS,DMS, MMS
  - How to teach “data sciences” for power systems? A first attempt in Fall 15 at TAMU

Acknowledgements

- Support from PSERC and BPA
- T-51 Team (Profs. M. Kezunovic, S. Grijalva, P. Chau) and Industry Advisors
- Collaborators:
  - Prof. Marc G. Genton (KAUST, Spatio-temporal Statistics)
  - Prof. P. R. Kumar (Texas A&M, System Theory)
- Students:
  - Yingzhong Gary Gu (GE)
  - Yang Chen (PJM)
  - Anupam Thatte (MISO)
  - Chen Nathan Yang (NYISO)
  - Meng Wu

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Thank You!

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