Spatio-temporal PV Forecast

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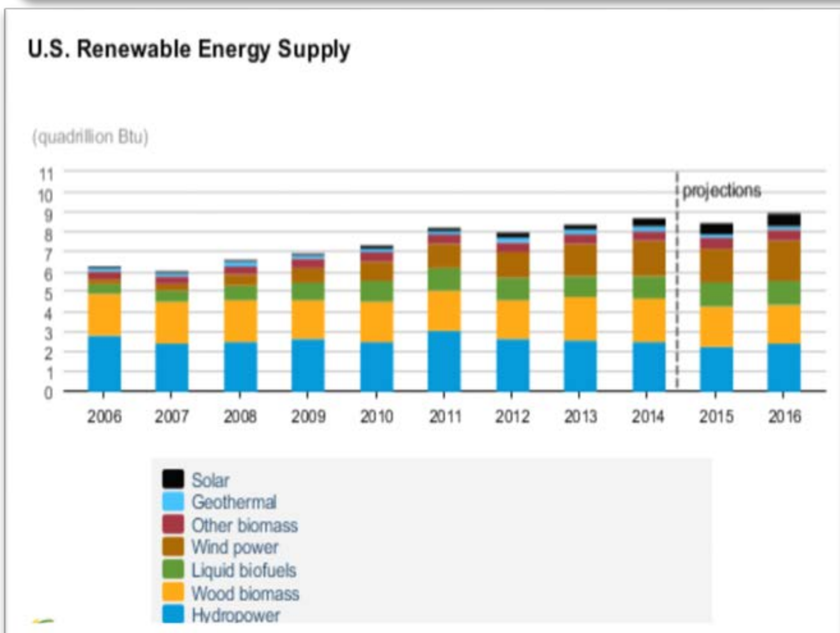
Presentation Outline

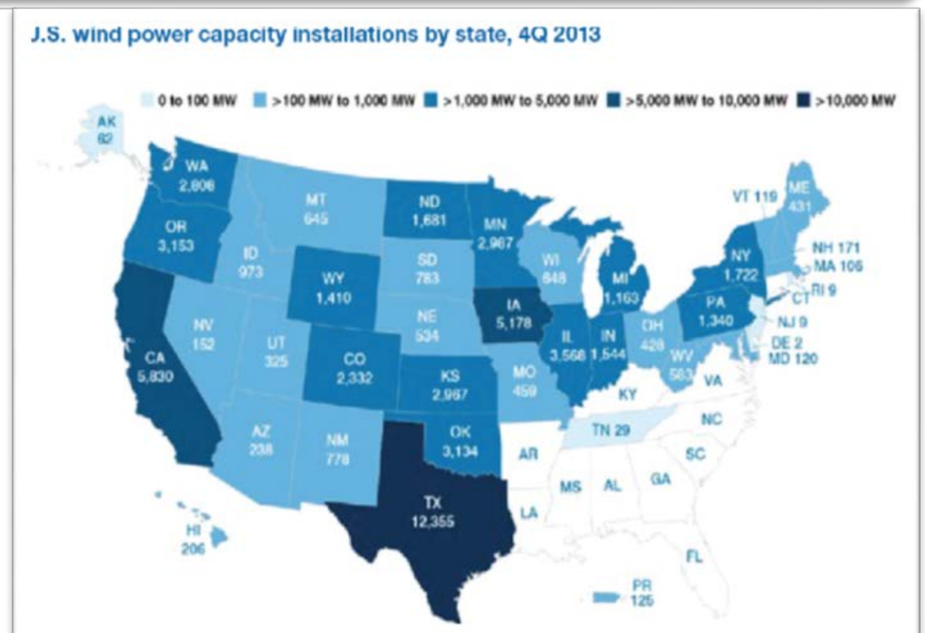
- **Motivation**
- **Spatio-temporal Correlations among Data Sets**
- **Case Study: PV (Photovoltaic) Forecast**
- **Other Ongoing Activities**
- **Concluding Remarks**

Growth of Renewable Generation

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).

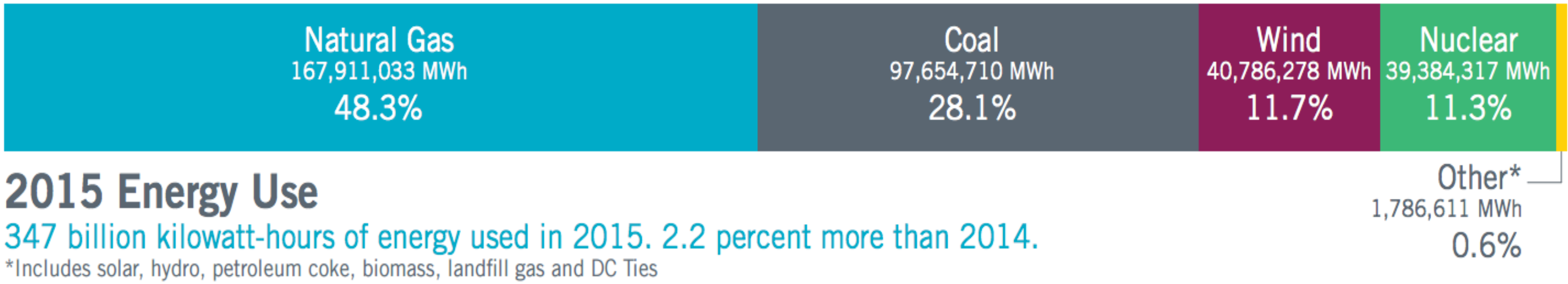




http://www.renewableenergyworld.com http://www.eia.gov
http://www.triplepundit.com/

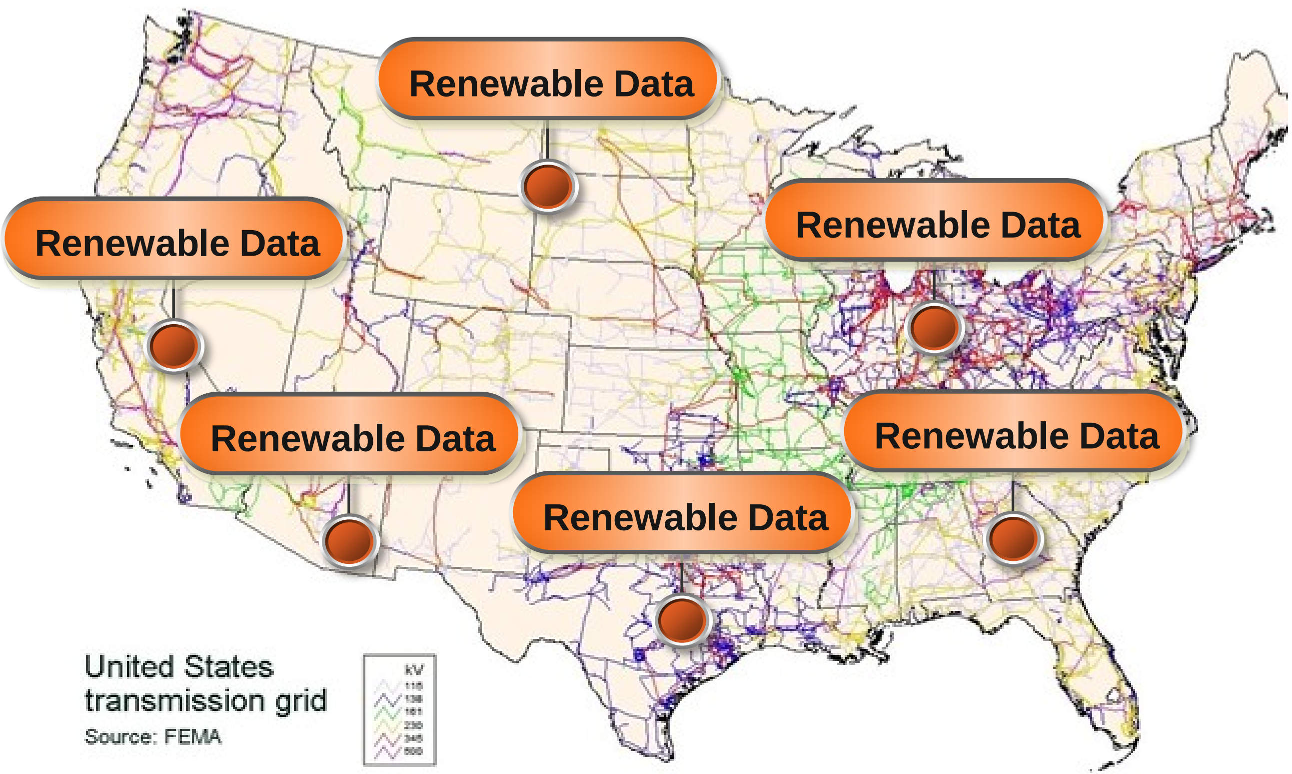
Electric Reliability Council of Texas (ERCOT) 2016

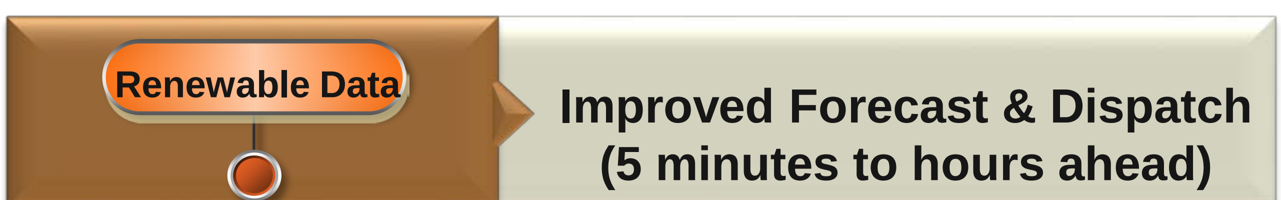
- Peak demand: 71,197 MW (August 15, 2016)
- Wind capacity: > 16,000 MW (*highest* of any state in the U.S.)
- Wind generation record: 14,023 MW, ~***49%*** of load at that time



http://ercot.com/content/news/presentations/2016/ERCOT_Quick_Facts

Spatio-temporal Correlations at Multi Scales





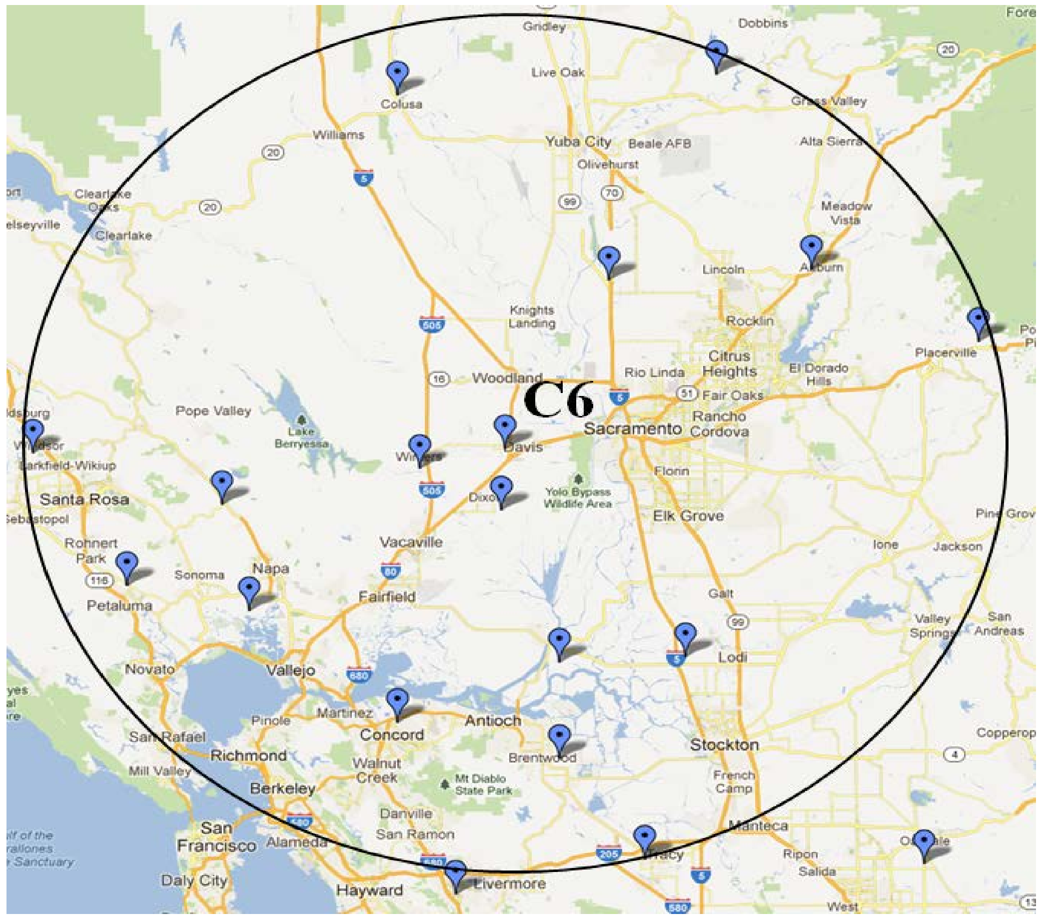
Case Study

- **Spatio-temporal Solar Forecast in Transmission System**

- **Spatio-temporal Solar Forecast in Distribution System**

Spatio-temporal Solar Forecast in Transmission System[2]

Sites Map



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

Spatio-temporal Solar Forecast in Transmission System[2]

ARX Model

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

Target Site

Neighboring Sites

We compared our model (ST ARX) 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.

Spatio-temporal Solar Forecast in Transmission System[2]

Simulation Results

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

2-hour-ahead Prediction Performance								
	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

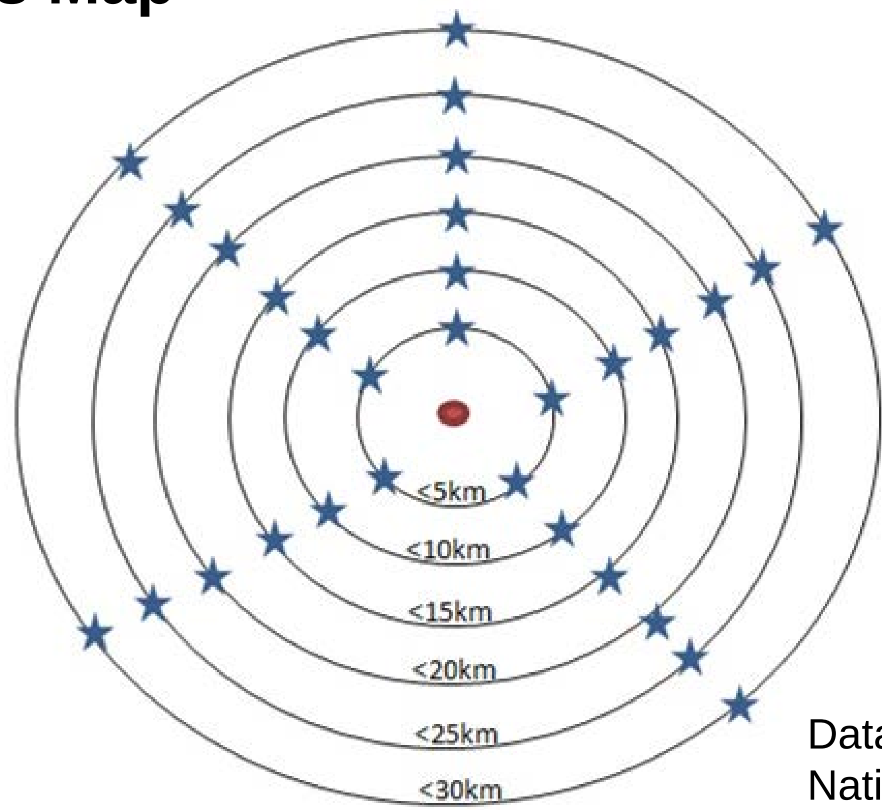
Shorter time-scale: Spatio-temporal is worse than PSS

Prediction Performance of Colorado Data								
	5 min		15 min		1 h		2 h	
Index	ST	PSS	ST	PSS	ST	PSS	ST	PSS
MAE	63.05	54.6	103.6	81.9	118.3	130.9	145.6	172.2
RMSE	106.9	104.7	154.8	148.6	163.2	182.1	187.6	221.8

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

Spatio-temporal Solar Forecast in Distribution System[3]

Sites Map



★ Neighboring Data Set

● Target Data Set (Austin)

Data Source:
National Solar Radiation Data Base

[3] Y. Li, A. Thatte, L. Xie,“Spatio-temporal Prediction of Solar Irradiance for Distribution Grid Operation,” (In Process).

Spatio-temporal Solar Forecast in Distribution System[3]

ARX Model

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

Averaged data within the distance range i

We compared our model (ST ARX) to auto-regression (AR) for multi-time-scale prediction.

[3] Y. Li, A. Thatte, L. Xie,"Spatio-temporal Prediction of Solar Irradiance for Distribution Grid Operation," (In Process).

Spatio-temporal Solar Forecast in Distribution System[3]

Simulation Results

Including the spatial neighboring inputs helps to improve the accuracy of prediction.

AR	ST ARX Model					
	Included Neighboring Input Distance (km)					
	<5 km	<10 km	<15 km	<20 km	<25 km	<30 km
20.15	19.52	19.53	19.21	19.16	19.27	19.09
Improve	3.1%	3.1%	4.7%	4.9%	4.4%	5.3%

ST ARX Performance Improvement						
Time Scale	Neighboring Input Distance (km)					
	<5 km	<10 km	<15 km	<20 km	<25 km	<30 km
0.5h	1.3%	0.9%	**2.1%**	2.0%	1.6%	1.8%
1h	3.1%	3.1%	4.7%	4.9%	4.4%	**5.3%**
2h	0.4%	1.7%	2.3%	2.2%	2.6%	**3.0%**

The optimal distance of spatial neighboring input is relatively long corresponding to the long time-scale prediction.

[3] Y. Li, A. Thatte, L. Xie,“Spatio-temporal Prediction of Solar Irradiance for Distribution Grid Operation.”

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:
  - Distribution-level Real-time OPF [4]
  - Large ramp events prediction

A Clean Slate Design of Dynamically Secure Distribution Grid

***Clusters of Microgrids as Intelligent Periphery*: Where innovations are likely to start and be tested**

Enabling Technologies

- Phasor network: μPMUs
- Voltage source inverter: Fast control of PCC voltage.

DSO: Distribution System Operator
PCC: Point of Common Coupling (interface between microgrid and main grid)

PMU & Power Electronics-enabled Control

Angle Droop Method at Point of Common Coupling (Proposed)

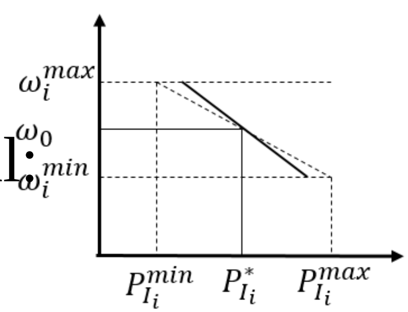
- Power balance indicator: angle deviation from PMU ref.
- Local frequency: load independent (quasistatic).
- Stability study result: A.S. in the large can be established.

VS.

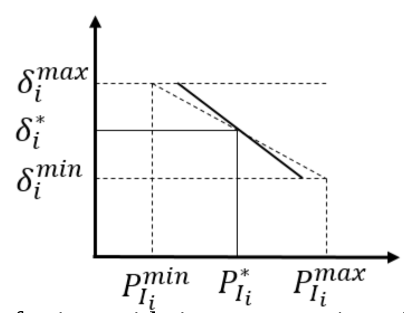
Frequency Droop Method (Conventional)

- Power balance indicator: frequency deviation from nominal.
- Local frequency: load dependent (quasistatic).
- Stability study result: regional asymptotic stability.

Conventional:



Proposed:



Y. Zhang and L. Xie, “Online dynamic security assessment of microgrids interconnections for future smart distribution,” *IEEE Transactions on Power Systems*, 2015 (in press)

Underlying Physical Model

Single SG Infinite Bus

Frequency Droop

$$\begin{bmatrix}\dot{\delta}\\ \dot{\omega}\end{bmatrix} = \begin{bmatrix}0 & 1\\ 0 & -\frac{D}{J}\end{bmatrix}\begin{bmatrix}\delta\\ \omega\end{bmatrix} - \begin{bmatrix}0\\ \frac{1}{J}\end{bmatrix}(P_I - P_I^*),$$

$$P_I = V_1^2 G_{11} + V_1 V_2 Y_{12} \sin\left(\delta + \frac{\pi}{2} - \theta_{12}\right),$$

$$P_I^* = V_1^2 G_{11} + V_1 V_2 Y_{12} \sin\left(\delta^* + \frac{\pi}{2} - \theta_{12}\right),$$

$$\dot{x} = Ax + B\phi(\delta),$$

$$x = [\delta \quad \omega]^T.$$

$$A = \begin{bmatrix}0 & 1\\ 0 & -\frac{D}{J}\end{bmatrix}, B = \begin{bmatrix}0\\ \frac{1}{J}\end{bmatrix} V_1 V_2 Y_{12},$$

$$\phi(\delta) = \sin\left(\delta + \frac{\pi}{2} - \theta_{12}\right) - \sin\left(\delta^* + \frac{\pi}{2} - \theta_{12}\right).$$

Multiple equilibriums!

$$\delta_e = C$$

$$\phi(\delta) = \phi(\delta + 2k\pi)$$

$$= \phi(\pi - \delta + 2k\pi)$$

Single Microgrid Infinite Bus

Angle Droop
PE-enabled

$$\dot{\delta} = -\frac{1}{\tau}(\delta - \delta^*) - \frac{\sigma}{\tau}(P_I - P_I^*),$$

$$P_I = V_1^2 G_{11} + V_1 V_2 Y_{12} \sin\left(\delta + \frac{\pi}{2} - \theta_{12}\right),$$

$$P_I^* = V_1^2 G_{11} + V_1 V_2 Y_{12} \sin\left(\delta^* + \frac{\pi}{2} - \theta_{12}\right).$$

$$\dot{x} = Ax + B\phi(y),$$

$$y = Cx.$$

$$x = \delta - \delta^*, y^* = \delta^* + \frac{\pi}{2} - \theta_{12}.$$

$$A = -\frac{1}{\tau}, B = -\frac{\sigma}{\tau} V_1 V_2 Y_{12}, C = 1.$$

$$\phi(y) = \sin(y + y^*) - \sin y^*$$

A.S. in the large can be achieved if σ sufficiently small!

$$x_e = 0 \Rightarrow \delta_e = \delta^*$$

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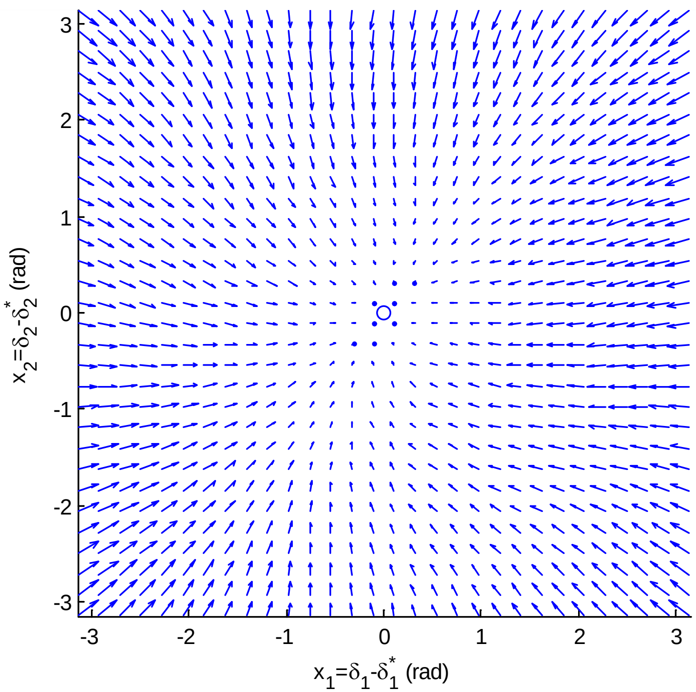
Standards for Transient Dynamics

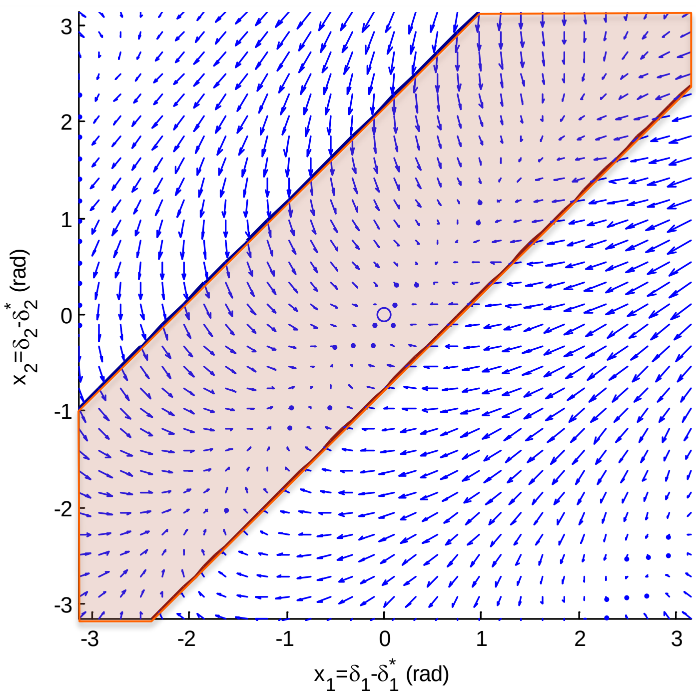
Smart Distribution Grid with Provable Transient Performance

1) $V_i \approx 1$ p.u.; 2) $\tau_{V_i} \gg \tau_{\delta_i}$.

- ***Theorem***: asymptotical stability (A.S.) ***in the large*** can be guaranteed if σ_{δ_i} of each interface is designed small.



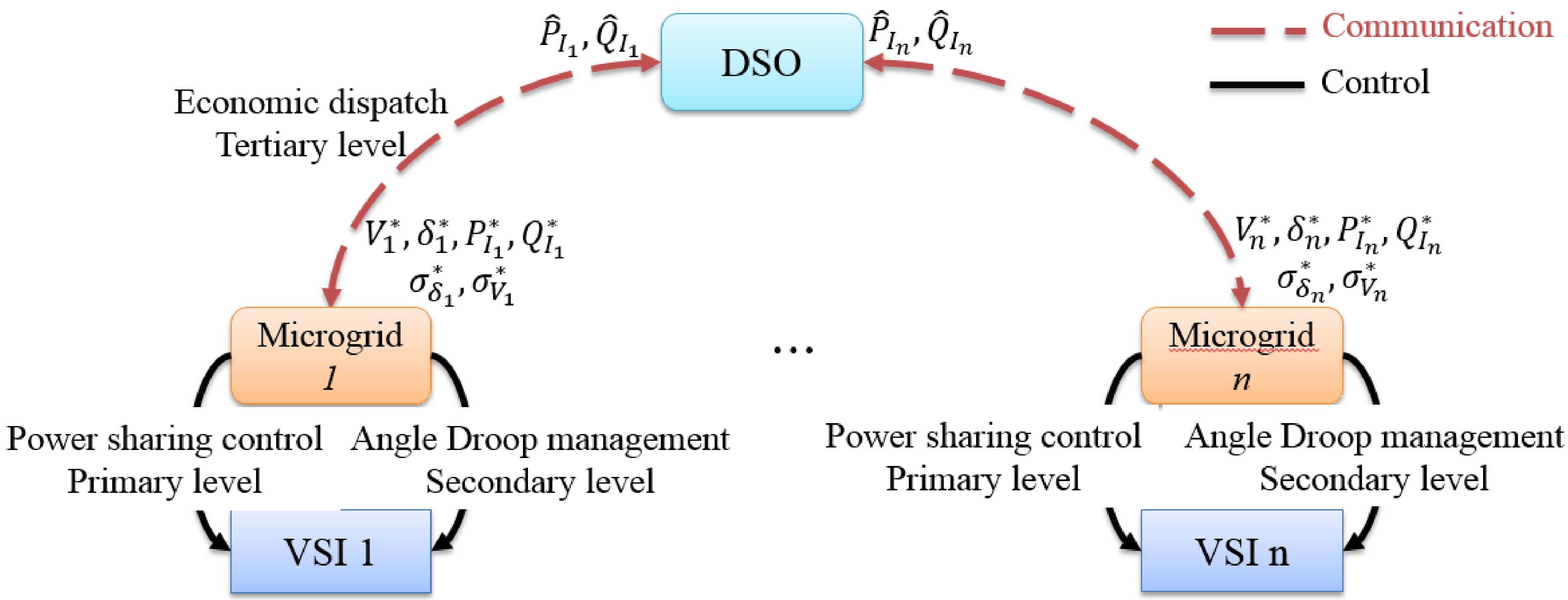
5% angle droop, sector [-1,1].



50% angle droop, sector [0,1].

Zhang and Xie, "Interactive Control of Coupled Microgrids for Guaranteed System-wide Stability," IEEE Transactions on Smart Grid, 2016.

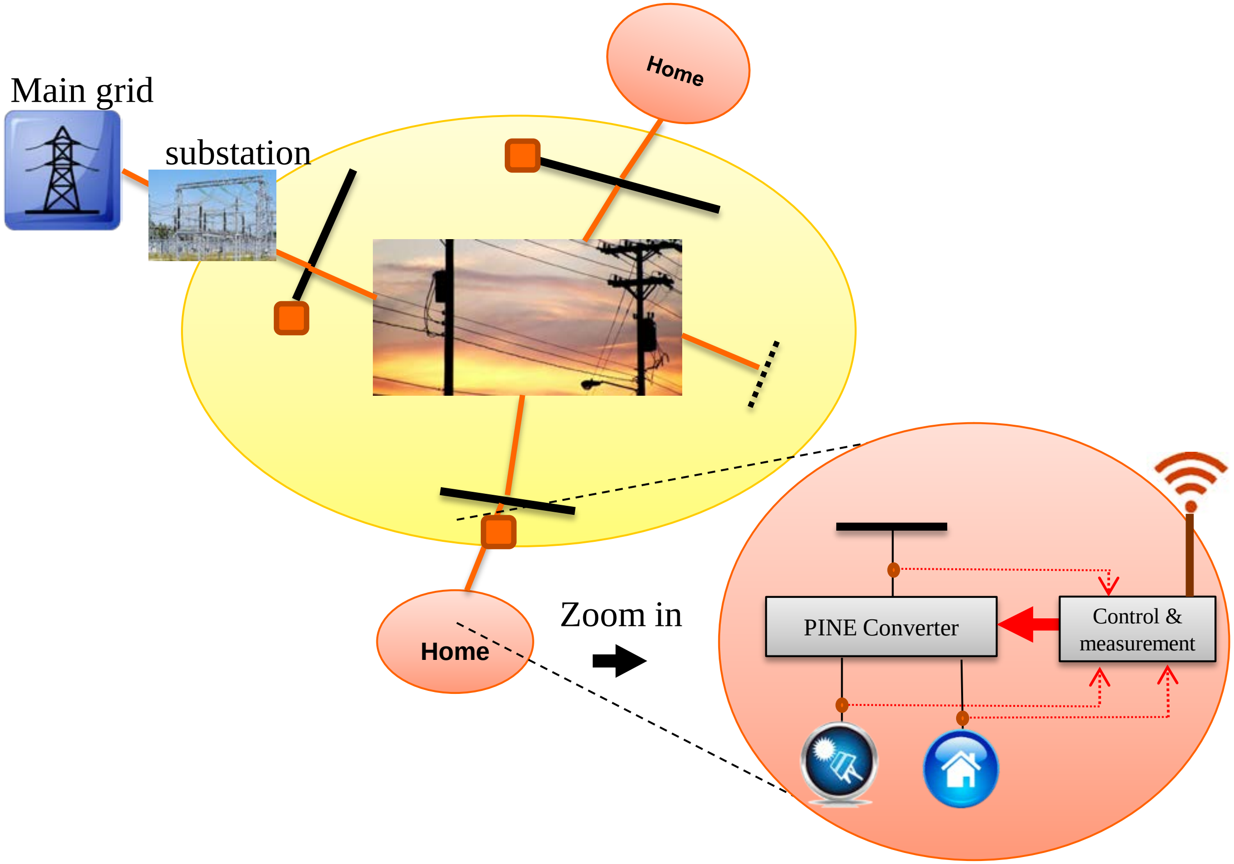
Control and Communication Architecture for Plug-n-Play Microgrids



DSO: Distribution System Operator. VSI: Voltage Source Inverter

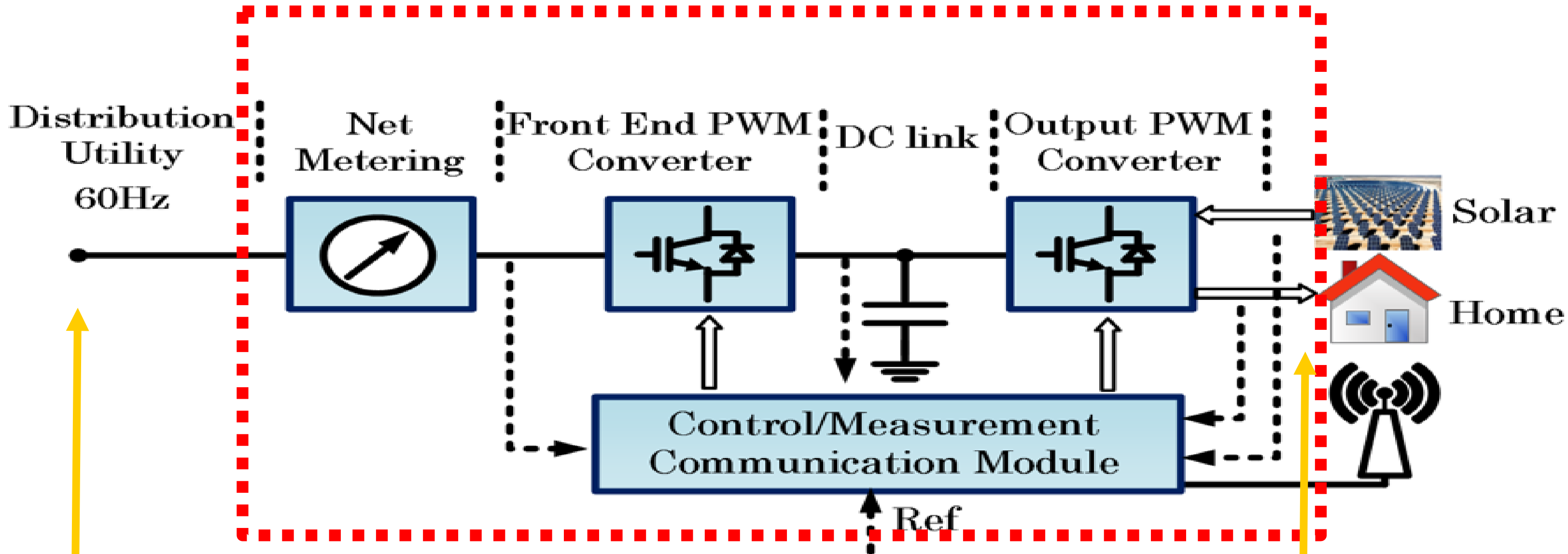
Y. Zhang and L. Xie, "Online dynamic security assessment of microgrids interconnections for future smart distribution," *IEEE Transactions on Power Systems*, 2015 (in press)

PINE: Power Electronics Intelligence at the Network edge

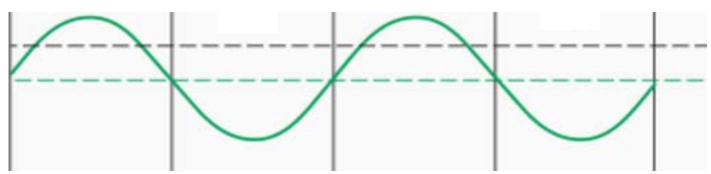


H. Chou, L. Xie, P. Enjeti, and P. R. Kumar, "Power Electronics Intelligence at the Network Edge," *ECCE 2017*

PINE Converter to Power Every Load in the Distribution System



Larger input voltage range
No harmonics
PF = 1 (adjustable)



Regulated voltage At the Output

H. Chou, L. Xie, P. Enjeti, and P. R. Kumar, "Power Electronics Intelligence at the Network Edge," *ECCE 2017*

References

[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.

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

[3] Y. Li, A. Thatte, L. Xie,"Spatio-temporal Prediction of Solar Irradiance for Distribution Grid Operation," TAMU Working Paper 2017-01.

[4] V. Seshadri Kumar, L. Xie, and P. R. Kumar, "An analytical approach for loss minimization and voltage profile improvement in distribution systems with renewable energy sources," *IREP Symposium* 2017.

Thank You !

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