TIME-SYNCHRONIZED STATE ESTIMATION AT THE GRID EDGE

North American SynchroPhasor Initiative (NASPI) Session #2 – Synchrophasor Projects and Edge Computing Solutions
Synchrophasors on the Edge: Edge Computing Solutions using Synchrophasors
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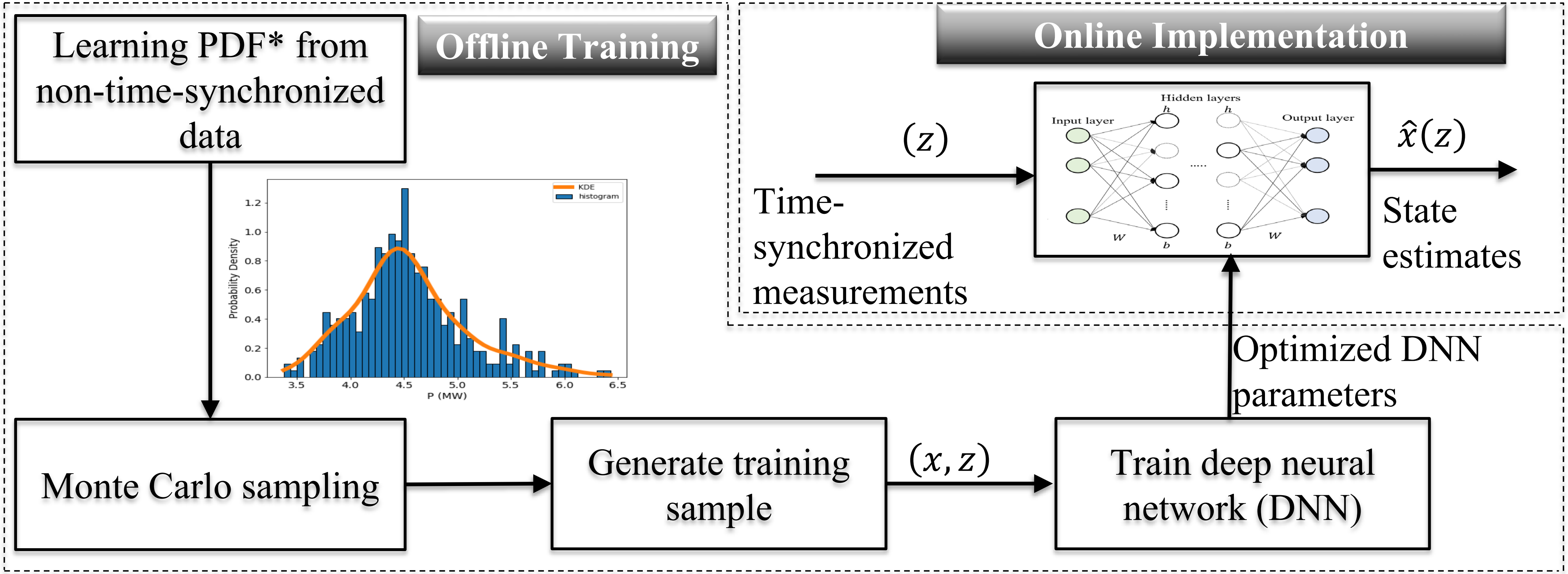
Time-Synchronized Distribution System State Estimation (DSSE)

- High-Speed Time-Synchronized DSSE facilitates:
  - Reverse Power Flow Detection
  - Topology Change Discovery
  - Fault Location Identification
  - High-Precision Control of Distributed Resources
- Challenges and Opportunities:

Type	Spatial Resolution	Temporal Resolution	Accuracy	Latency
SCADA	Feeder head	1 to 10 seconds	Medium	2 to 4 seconds
Smart meter	Dense	15 minutes to hourly	Low	Few hours to days
Phasor measurement unit (PMU)/micro-PMU/D-PMU	Extremely sparse	Milliseconds	High	Negligible
Solar photo-voltaic meter	Relatively sparse	15 minutes to hourly	High	≥ 15 minutes

Schematic of the Proposed Methodology[1]



*PDF: probability density function

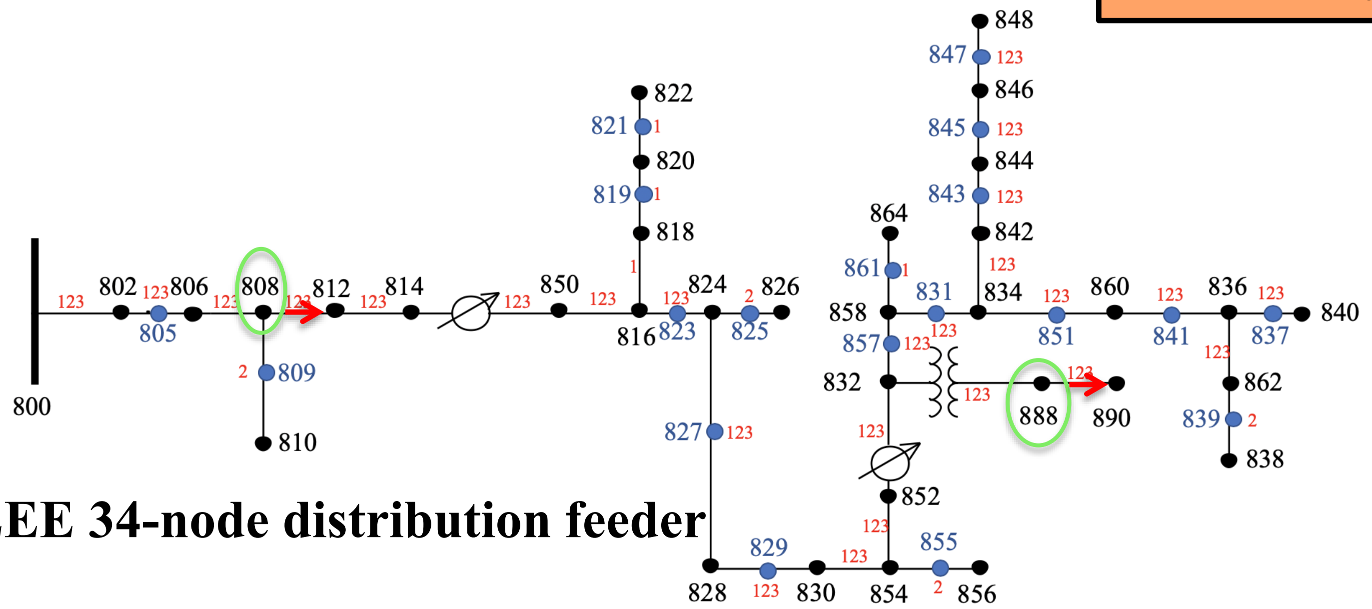
- Non-time-synchronized data is only used to generate sample data to train the DNN (Offline operation)
- Time-synchronized measurements are used in the testing stage (Online operation)
- Does not require complete observability by synchrophasors

[1] B. Azimian, R. S. Biswas, A. Pal, and L. Tong, "Time synchronized distribution system state estimation for incompletely observed systems using deep learning and realistic measurement noise," presented at *IEEE Power Eng. Soc. General Meeting*, 2021.

DSSE with Two Synchrophasors in IEEE-34 Node Feeder

- **Distribution System Characteristics:**
  - Single, double and three phase unbalanced Wye-Delta loads
  - ZIP load models
  - Voltage regulators
  - Step down voltage transformer
  - Single, double, and three phase laterals

- **Deep Neural Network (DNN) Characteristics:**
  - 5 Hidden layers – 400 neurons/layer
  - ReLU activation function for hidden layers
  - Linear activation function for output layer
  - Optimizer: ADAM
  - Empirical mean squared error loss function
  - 8k training, 2k validation, 2.5k test samples



IEEE 34-node distribution feeder

Line monitored by synchrophasor

Distributed loads

Regulator

Transformer

1 A-phase
2 B-phase
3 C-phase

Results of DNN-based DSSE for IEEE-34 Node System

Results for Linear State Estimation (LSE) and Proposed DNN-based DSSE*

Method	Magnitude MAPE (%)	Phase MAE (degrees)	#Synchrophasor
Linear State Estimation (LSE)	0.25	0.14	26[2]
DNN-based DSSE	0.24	0.10	2

* When measurement noise is Gaussian

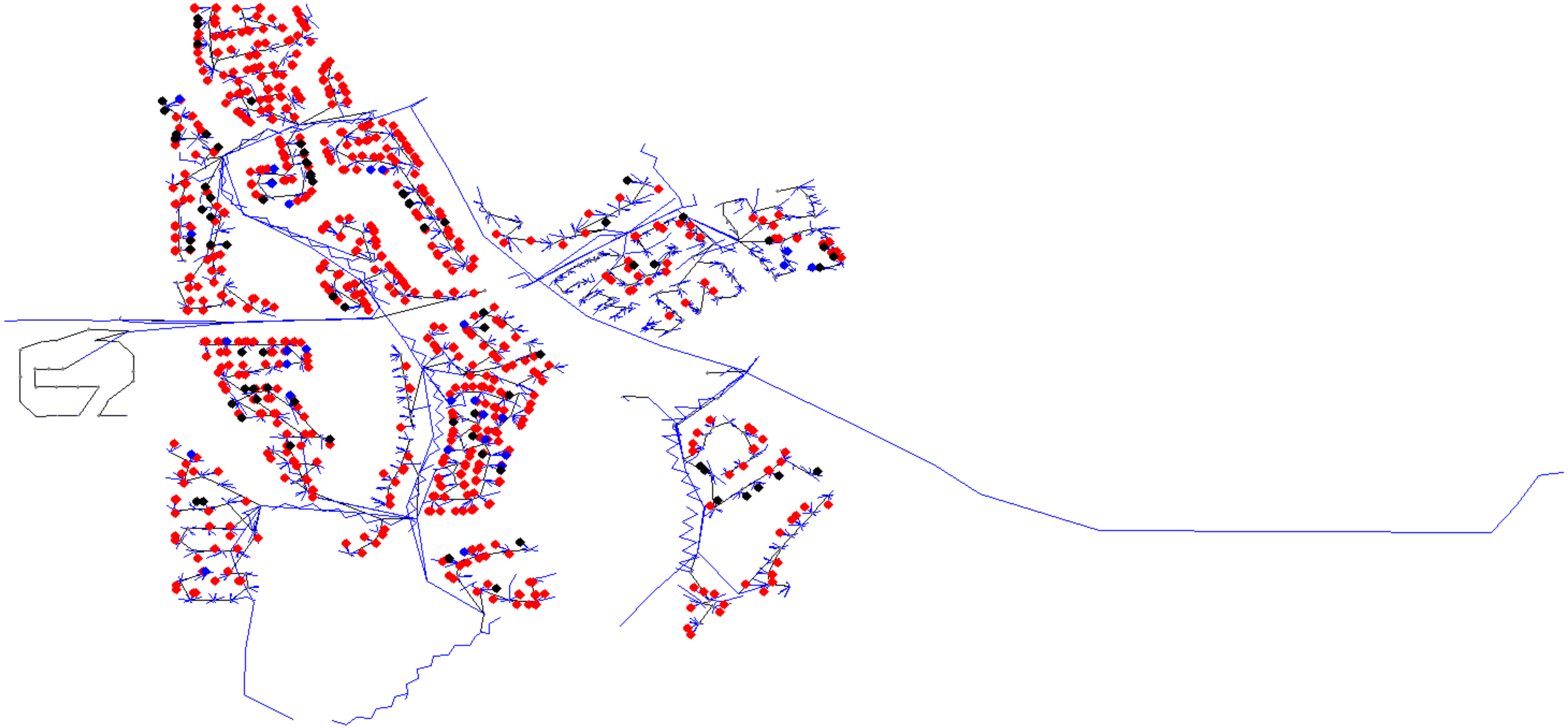
DNN-based DSSE Results Under Gaussian and Non-Gaussian Noise Environments

Method	Magnitude MAPE (%)	Phase MAE (degrees)	#Synchrophasor
DNN-DSSE Gaussian	0.24	0.10	2
DNN-DSSE Non-Gaussian	0.24	0.11	2

$$MAPE = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{y_j - \hat{y}_j}{y_j}\right| \qquad MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|$$

[2] R. S. Biswas, B. Azimian, and A. Pal, “A micro-PMU placement scheme for distribution systems considering practical constraints,” in *Proc. IEEE Power Eng. Soc. General Meeting*, Montreal, Canada, pp. 1-5, 2-6 Aug. 2020.

Secondary Distribution Feeder Network of an Actual Utility



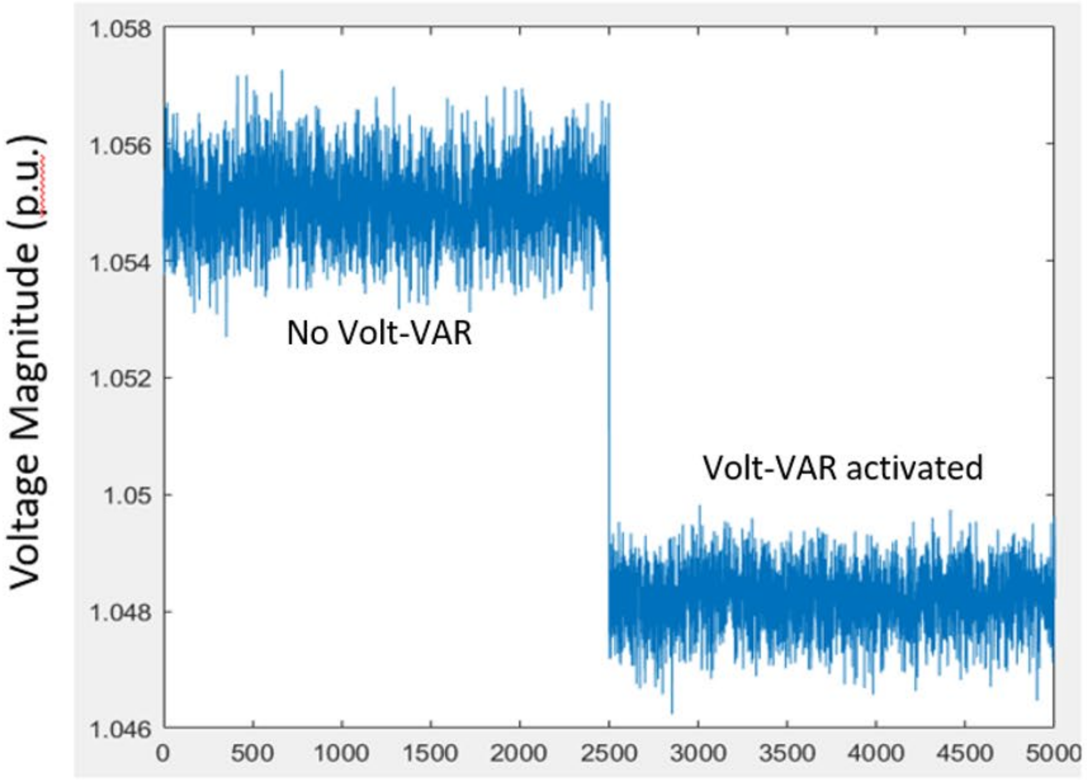
- March 15th 2:00 PM
- 9586 state variables (4793 voltage magnitude + 4793 voltage angle)
- 766 PVs, of which 120 are equipped with Volt-VAR controller

	Phase MAE [degree]	Magnitude MAPE [%]
DNN-DSSE Non-Gaussian	0.0264	0.0278

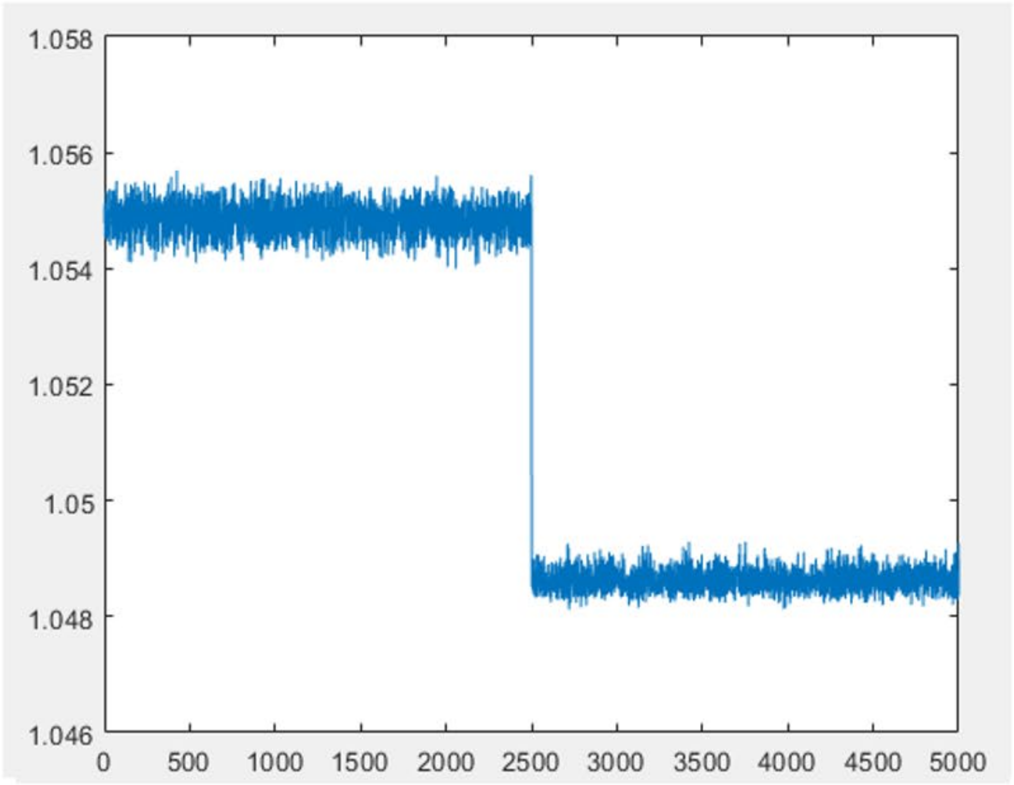
DNN-based DSSE Results with Volt-VAR Control

	Phase MAE [degree]	Magnitude MAPE [%]
DSSE Results with Volt-VAR control modeled	0.0270	0.0380

True voltages



Estimated voltages



True and estimated voltage magnitudes at a particular node in the system


THANK
YOU