



# Machine Learning Based State Estimation for Transmission Systems

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EPRI

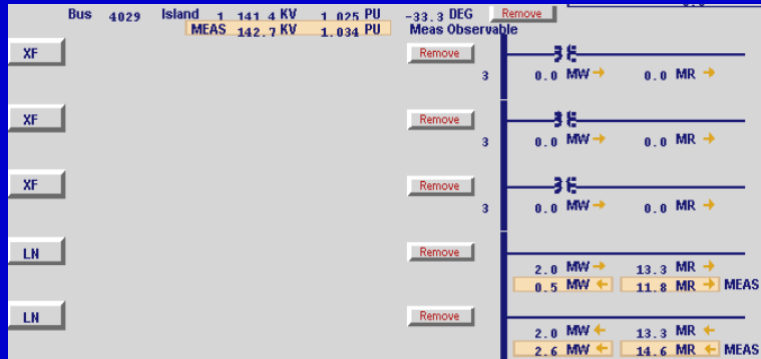
Panel Session: “Application of Big Data and AI/ML in Monitoring,  
Operations, Planning and Protection”  
IEEE PES General Meeting  
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Acknowledgments: Prof. Anamitra Pal (ASU)

# State Estimation

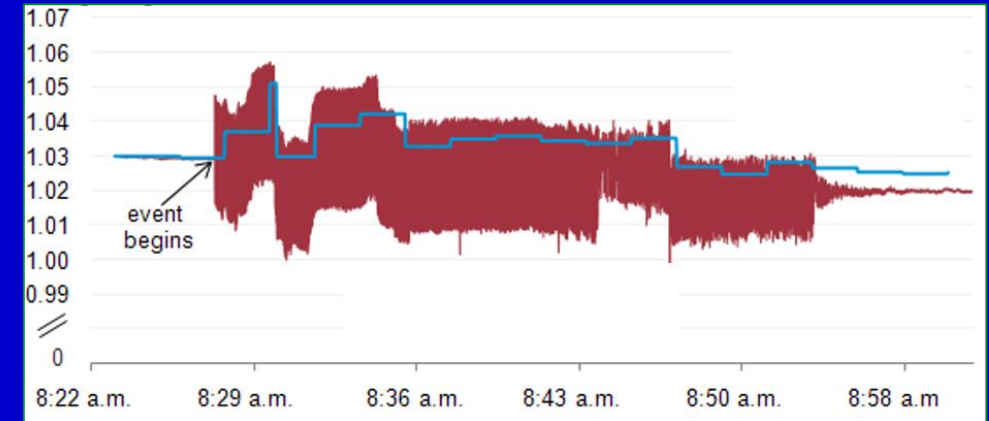
## Backbone EMS Function for Situational Awareness

### SCADA/EMS State Estimation



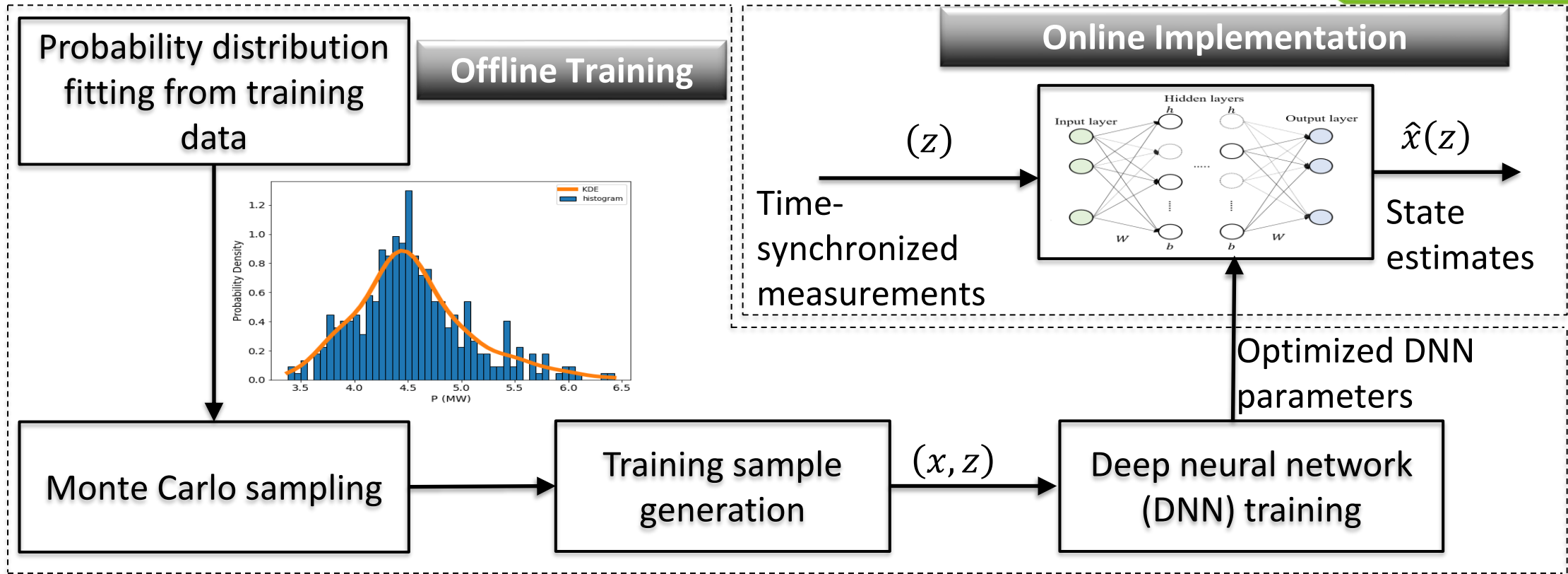
- **State Definition:** Positive sequence voltage phasors (bus voltage magnitudes and angles) of system's buses
- **Measurement Set:** SCADA data
  - Voltage magnitude, current magnitude, real & reactive power flows and injections
  - Measurement model: Nonlinear
  - Gaussian distribution of measurement error
- **Solution Algorithm:** Weighted Least Squares
  - Iterative Solution

### PMU Based State Estimation



- a.k.a Linear State Estimation
- **Measurement Set:** Phasor Measurement Unit (PMU)
  - Voltage and current phasors
  - Measurement model: Linear
  - Gaussian distribution of measurement error
- **Solution Algorithm:** Weighted Least Squares
  - Direct Solution

# Machine Learning Based State Estimation



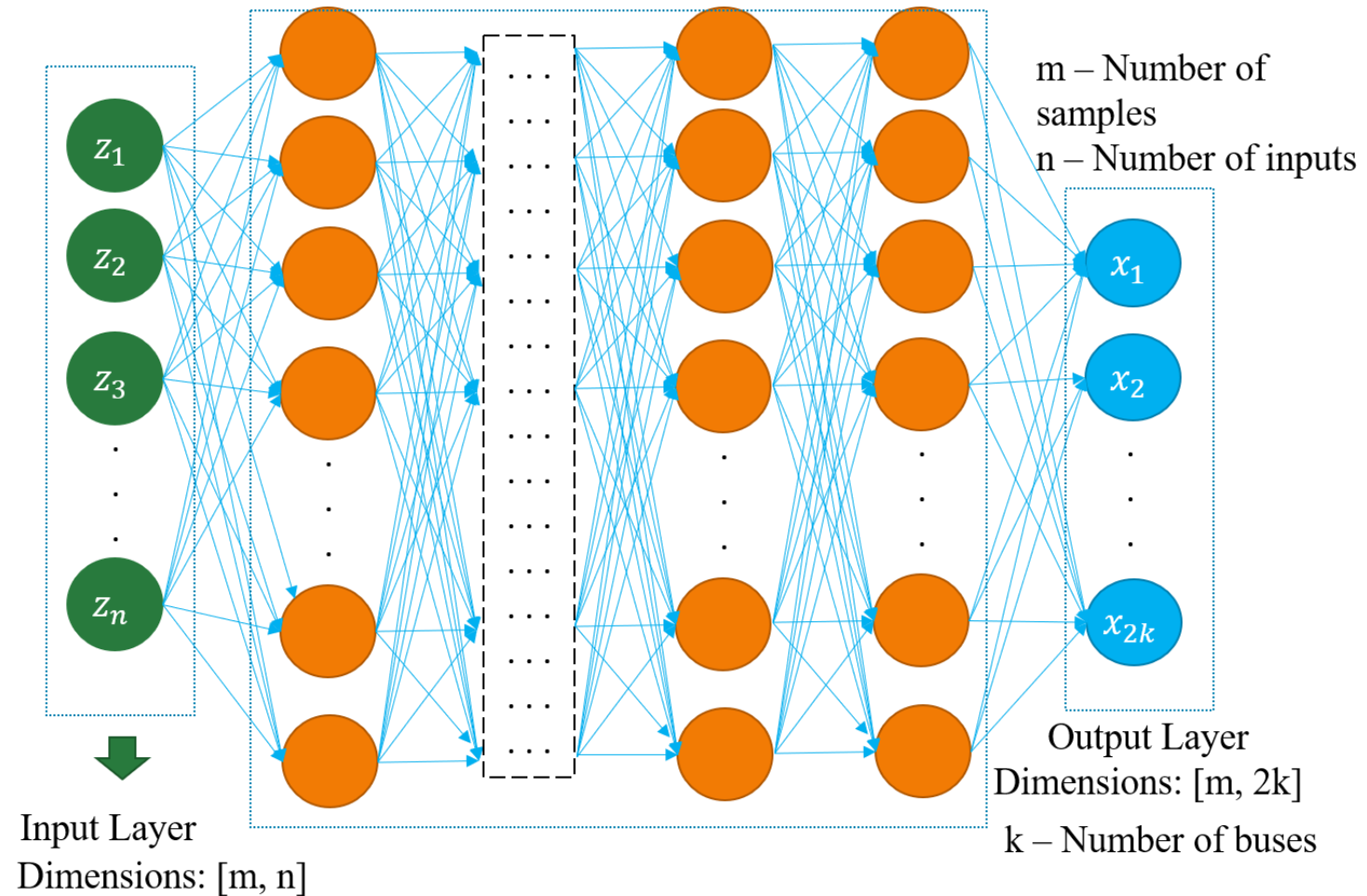
## Features

- Model Independent
- Independent of Measurement Error Distribution
- Overcomes SCADA/PMU Synchronization Issues
- Achieves Full System Observability with Limited Number of PMUs
- High Speed



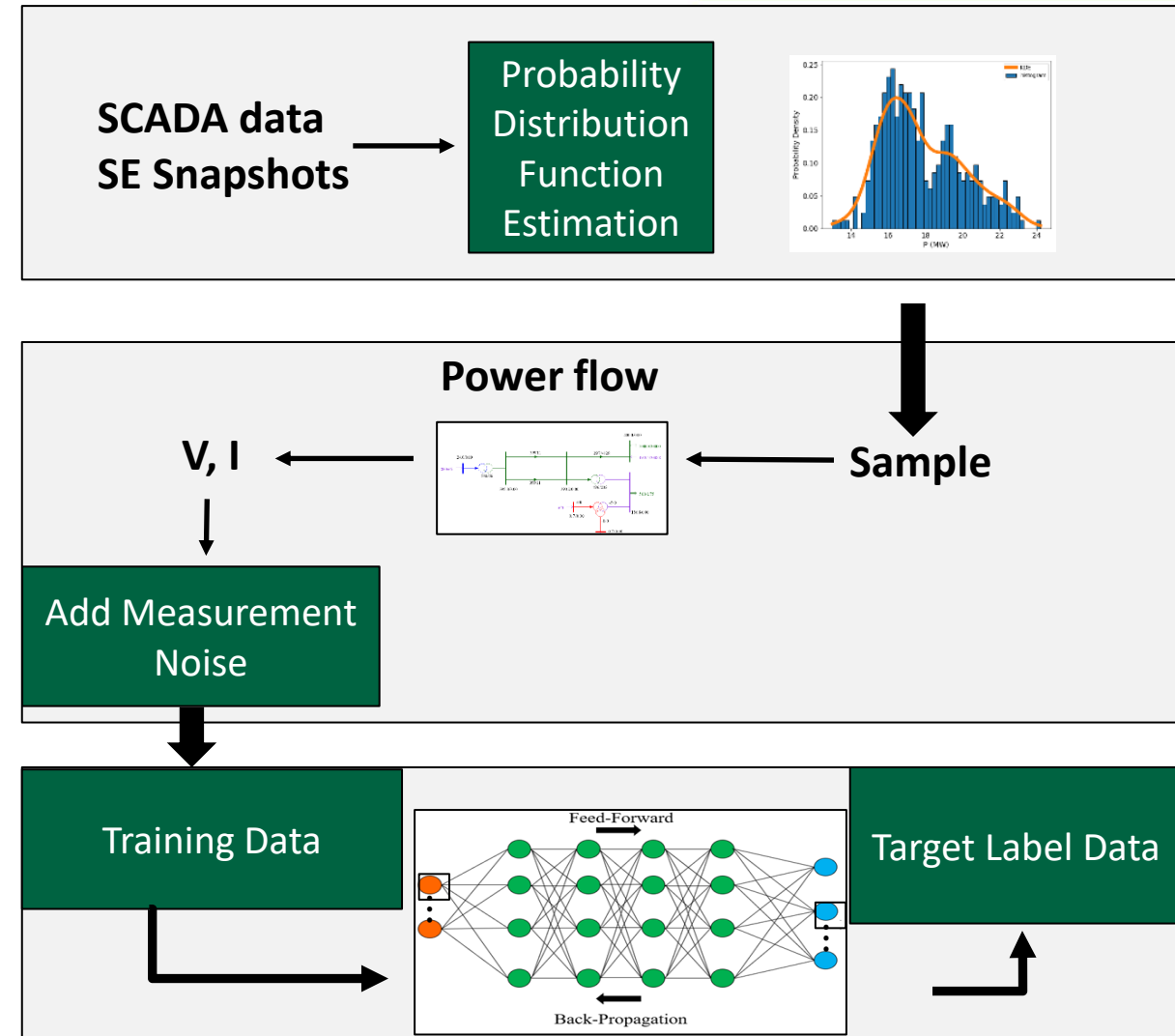
# Deep Neural Network (DNN)

- DNN Input: PMU measurements
- DNN Output: States of the system
- Target accuracy:
  - $<0.1\%$  error in magnitude
  - $<0.5^\circ$  error in angle



# DNN Training

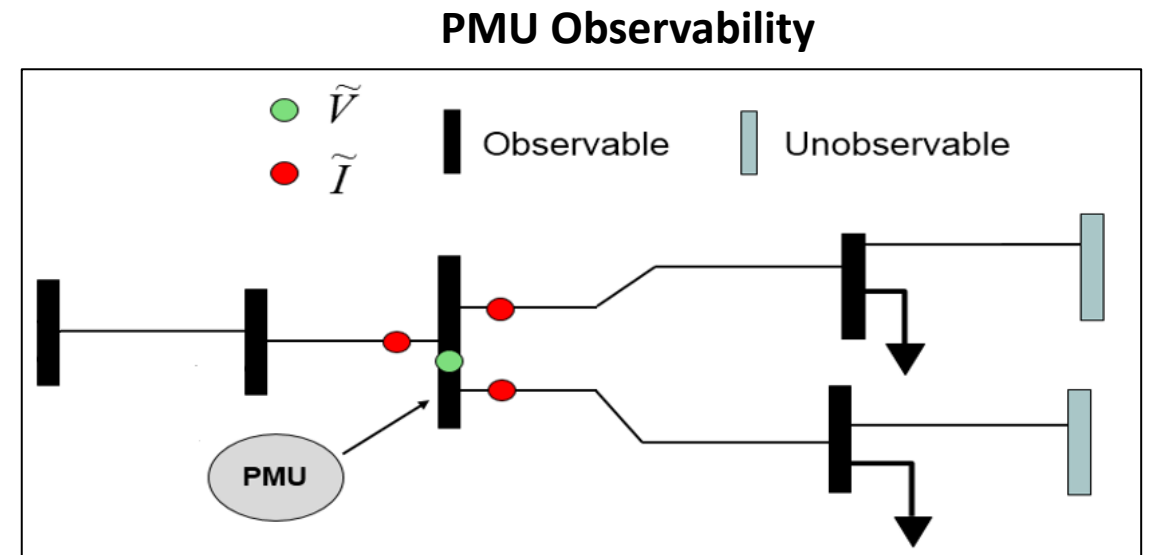
- Collect historical SE data (Load, generation, system model)
- Probability distribution function fitting
- Monte Carlo sampling and PF/OPF solution
- Embed noise functions to mimic instrumentation errors: “Synthetic Measurements”
- Identify dominant topologies
- Train DNN hyperparameters for base topologies and specific PMU placement



# LSE vs ML-SE - Topological Observability

## Full Grid Observability with Limited Number of PMUs

- Linear State Estimation (LSE): number of estimated states depends on topological observability from PMUs
- ML based SE: entire system state estimation without need for topological observability

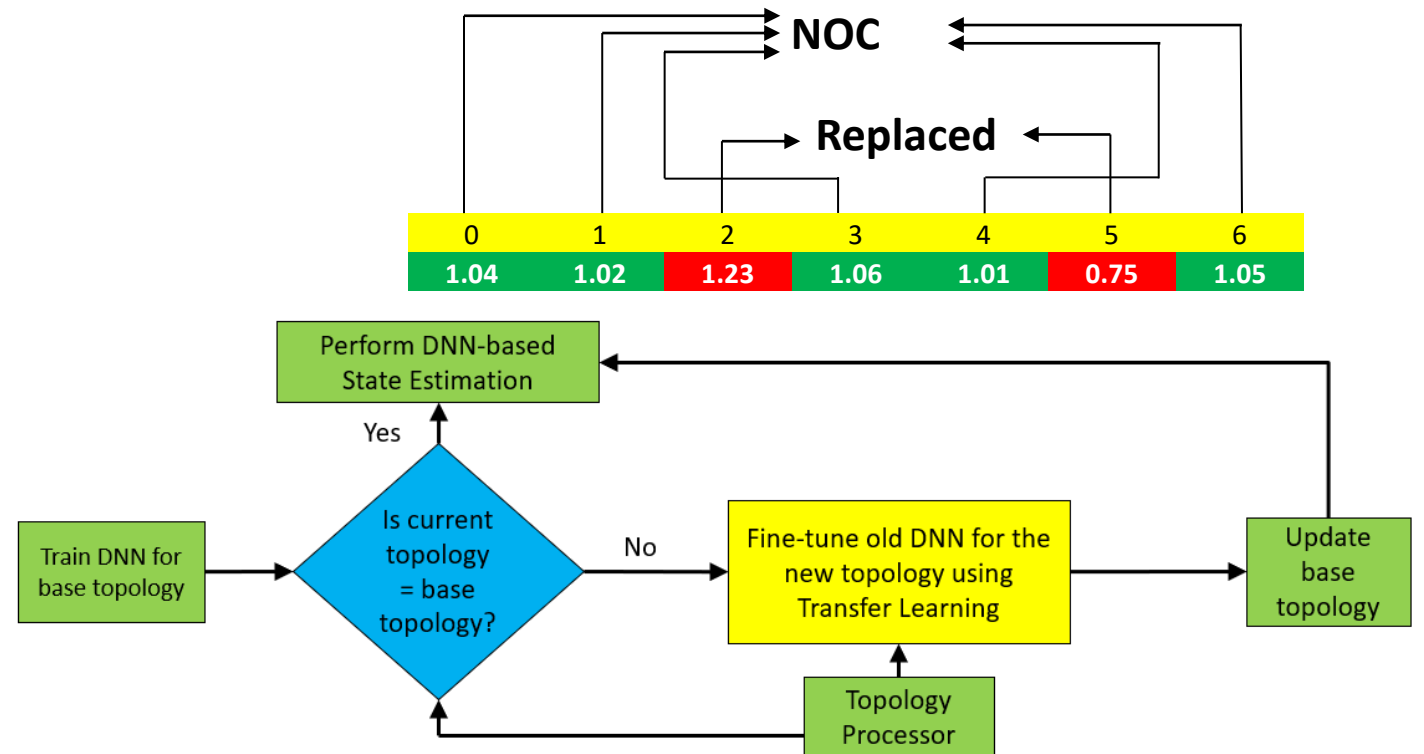
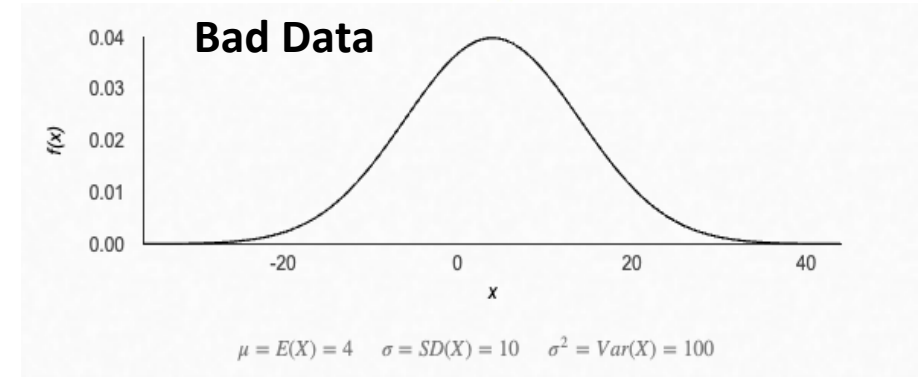


## 118 Bus System – Estimation Error

Scenario	LSE	ML-SE
<b>Metric</b>	<b>32 PMUs</b>	<b>13 PMUs</b>
Voltage Magnitude	0.001 p.u.	0.001 p.u.
Voltage Angle	0.00199 rad	0.0020 rad

# Bad/Missing Data & Topology Changes

- Bad/Missing data detection based on Wald Test
- Bad/Missing data replacement with Nearest Operating Condition (NOC) from training dataset
- Transfer Learning used for DNN update when topology changes



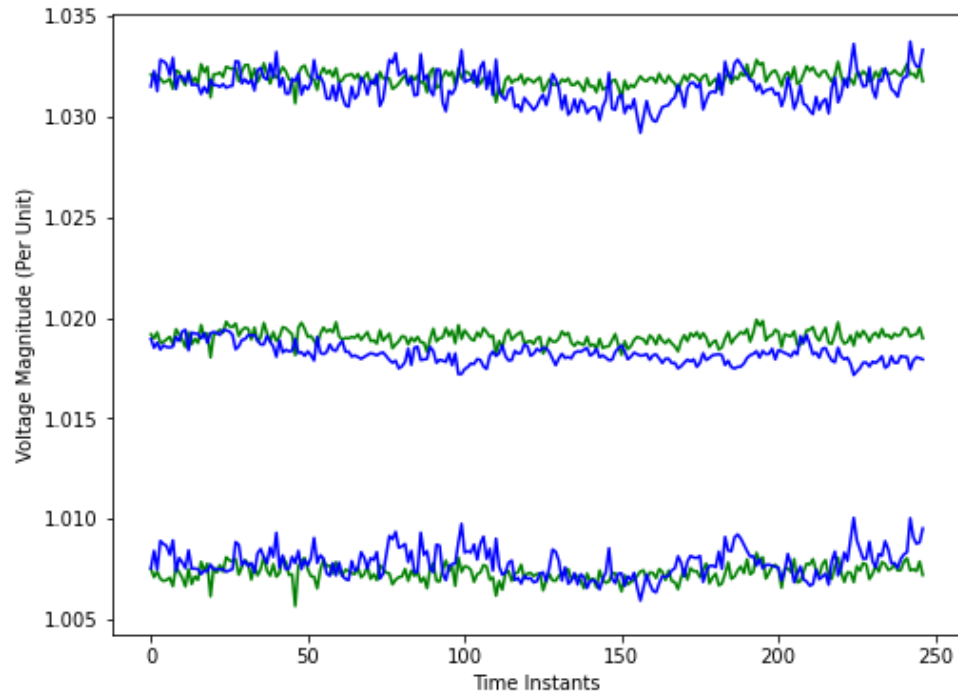
# TVA Case Study – Preliminary Results

## Provided data:

- EMS SE snapshot files (PSS/E format): July 1 to December 31, two files per day
- PMU data: 709 PMUs. 1 hour for 15<sup>th</sup> day of August-December

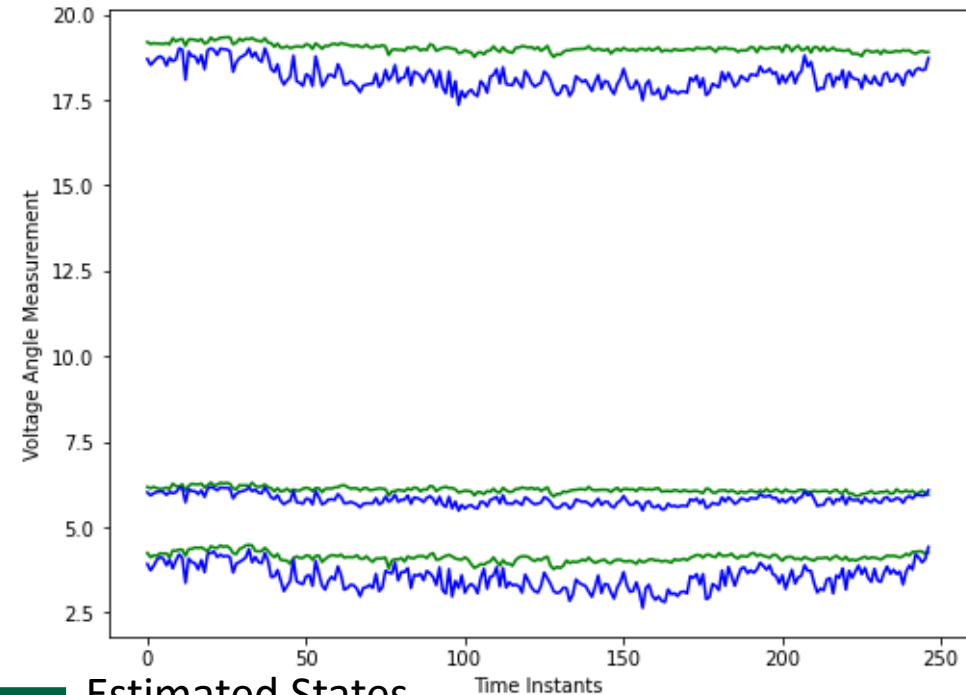
kV Level	# of PMUs
500	130
345	3
230	15
161	517
<=135	44

Voltage magnitude (Per unit)



PMU Measurements

Voltage angle (Degrees)



Estimated States